FACTORS INFLUENCING ADOPTION AND USAGE PROBABILITY OF CAR SHARING IN BANGKOK

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ปัจจัยส่งเสริมการใช้และความน่าจะเป็นของบริการคาร์แชริ่งในกรุงเทพมหานคร

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ปวีณา ร่วมชาติ : ปัจจัยส่งเสริมการใช้และความน่าจะเป็นของบริการคาร์แชริ่งในกรุงเทพมหานคร. (FACTORS INFLUENCING ADOPTION AND USAGE PROBABILITY OF CAR SHARING IN BANGKOK) อ.ที่ปรึกษาหลัก : รศ. ดร.มาโนช โลหเตปานนท์, อ.ที่ปรึกษาร่วม : รศ. ดร.พงศา พรชัยวิเศษกุล

งานวิจัยนี้มีวัตถุประสงค์เพื่อหาปัจจัยส่งเสริมการใช้และความน่าจะเป็นของบริการคาร์แชริ่งในกรุงเทพ ซึ่งงานวิจัยนี้ได้แบ่งการศึกษาออกเป็น 2 ขั้นตอน โดยงานวิจัยแรกมีวัตถุประสงค์เพื่อศึกษาปัจจัยที่มีผลต่อความน่าจะเป็นในการเลือกใช้บริการคาร์แชริ่ง และงานวิจัยที่สองมีวัตถุประสงค์เพื่อศึกษาทัศนคติของผู้ใช้บริการที่มีผลต่อความตั้งใจใช้บริการคาร์แชริ่ง โดยทั้งสองงานวิจัยเป็นการวิจัยเชิงปริมาณ

งานวิจัยที่ 1 ได้ทำการเก็บข้อมูลทั้งสิ้น 612 ตัวอย่าง จากกลุ่มประชากรเป้าหมายคือ ผู้ที่มีอายุมากกว่า 18 ปี ที่อาศัย เรียน หรือทำงาน ในกรุงเทพมหานคร โดยใช้แบบสอบถามเป็นเครื่องมือในการวิจัย ใช้สถิติการวิเคราะห์การถดถอยพหุคูณภายใต้แนวคิดของการวิเคราะห์การถดถอยโลจิสติกส์ ซึ่งปัจจัยที่ใช้ทดสอบแบ่งเป็น 3 กลุ่ม คือ ลักษณะประชากรศาสตร์ ลักษณะการเดินทาง และความสนใจบริการคาร์แชริ่ง ผลการวิจัยพบว่า ลักษณะประชากรศาสตร์ไม่ส่งผลต่อการตัดสินใจใช้บริการคาร์แชริ่ง ส่วนปัจจัยที่ส่งผลต่อความน่าจะเป็นที่ผู้ใช้บริการจะเลือกใช้บริการคาร์แชริ่ง ได้แก่ รูปแบบการเดินทาง วัตถุประสงค์การเดินทาง ระยะเดินจากจุดจอดรถไปยังบ้านหรือที่ทำงาน ประสบการณ์ในการใช้บริการแท็กซี่ผ่านแอปพลิเคชั่น ประสบการณ์ในการใช้บริการคาร์แชริ่ง กิจกรรมที่จะใช้บริการคาร์แชริ่ง เหตุผลที่จะใช้คาร์แชริ่ง ระยะเวลารอคอยรถที่นานที่สุดที่ยอมรับได้ในการใช้บริการคาร์แชริ่ง และราคาของการใช้บริการคาร์แชริ่ง

งานวิจัยที่ 2 ได้ศึกษาทัศนคติของผู้ใช้บริการที่มีผลต่อความตั้งใจใช้บริการคาร์แชริ่ง ภายใต้กรอบแนวคิดการยอมรับเทคโนโลยี โดยเพิ่มตัวแปรภายนอก 4 ตัว ได้แก่ นวัตกรรมส่วนบุคคล ความห่วงใยต่อสิ่งแวดล้อม อิทธิพลทางสังคม และการรับรู้ความเสี่ยง ทำการเก็บข้อมูลโดยใช้แบบสอบถาม ได้ข้อมูลทั้งสิ้น 505 ตัวอย่าง ใช้เทคนิคการวิเคราะห์ปัจจัยยืนยัน (CFA) และโมเดลสมการโครงสร้าง (SEM) ในการวิเคราะห์ข้อมูล โดยผลการวิจัยพบว่า ผลลัพธ์ไม่ได้ยืนยันกรอบแนวคิดการยอมรับเทคโนโลยีดั้งเดิม เนื่องจากไม่พบความสัมพันธ์ระหว่างการรับรู้ความง่ายในการใช้งานกับทัศนคติในการใช้บริการคาร์แชริ่ง อย่างไรก็ตามผลการวิจัยพบว่าตัวแปรภายนอกทั้งสี่ตัวมีอิทธิพลต่อความตั้งใจใช้บริการคาร์แชริ่ง

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This thesis aimed to examine factors influencing adoption and usage probability of car sharing in Bangkok. There were two phases of study. The first phase was examining the factors influencing the probability of using of car sharing. The latter was designed to assess customers’ attitudes toward the intention to use car sharing. Both studies employed a quantitative method of data collection and analysis.

Study One assessed the likelihood of using car sharing from customers’ characteristics in three main groups: socio-economic status, travel behavior and car-sharing preferences. The data were collected through a questionnaire with the target population group. In total, there were 612 observations. Then, the data were analyzed using descriptive statistics and multiple linear regression analysis under the concept of logistic regression. Through multiple linear regression analysis, the results indicated that the respondents’ socio-economic status did not affect the probability of car-sharing adoption. However, travel behavior and car-sharing preferences affected the probability of car-sharing adoption.

Study Two investigated latent attitudes influencing the users’ intention to use car sharing. This study utilized an extended technology acceptance framework with four external variables: personal innovativeness (PI), environmental concern (EC), social influence (SI) and perceived risk (PR). Similarly, the survey was conducted to collect the data from target population group. In total, 505 participants completed the questionnaire. Confirmatory factor analysis (CFA) and structural equation model (SEM) techniques were adopted for data analysis. The results did not confirm the original TAM since a relationship was not found between perceived ease of use (PEOU) and attitude toward car sharing (ATT). However, the results supported that all four external variables influenced the intention to use car sharing.

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Chapter 1

Introduction

1.1 Rationale

Nowadays, more and more people are migrating to the city center, particularly Bangkok, to work or study. The population in Bangkok is rising every year and up to 5.5 million by December 2018 (Administrative Strategy Division, 2019). Moreover, there are also nonregistered population in Bangkok over two million people (National Statistics Office Thailand, 2018). There are not only in Bangkok, surrounding provinces also held millions of people.

Bangkok's passenger transport is dominated by private vehicles, especially automobiles, pickup trucks and motorcycles. The majority of the sample group for the current research traveled in Bangkok and its surrounding provinces by private car, accounting for 39.90%, followed by public transport (29.50%) and private motorcycles (23.80%), according to the Transport and Traffic Planning and Policy Office (2018).

The number of private vehicles in Bangkok increased at an average of 8% to 10% per year from 2008 to 2018 and this trend is expected to continue (Figure 1). By the end of 2018, there were more than 10 million registered vehicles in Bangkok (Department of Transport, 2018).

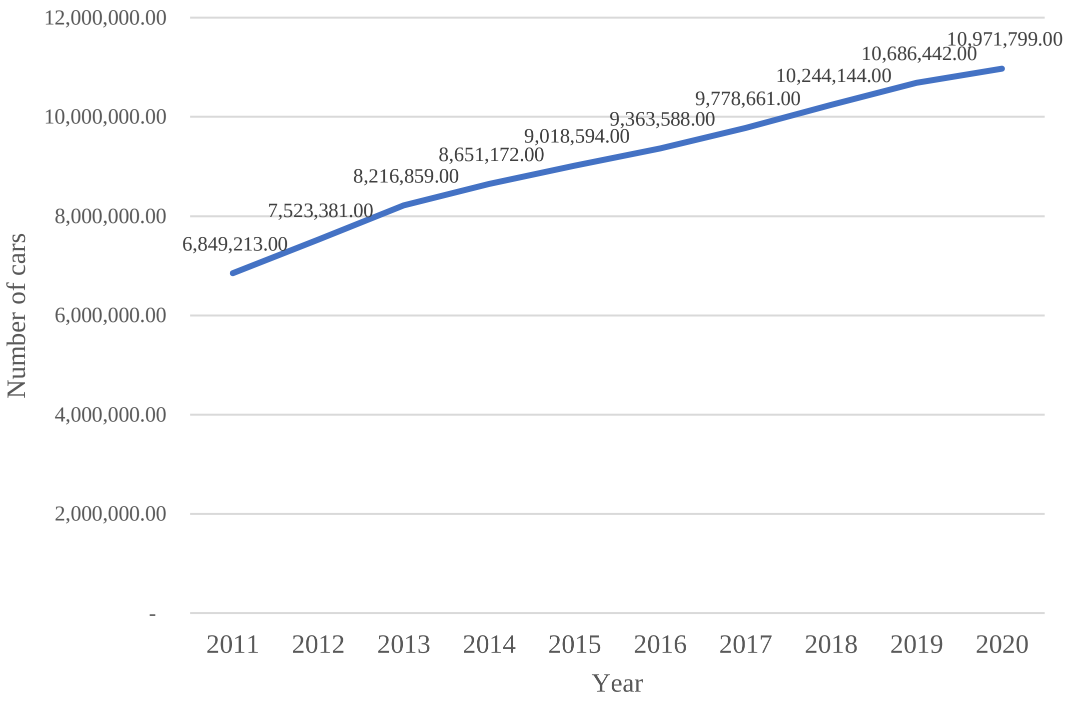
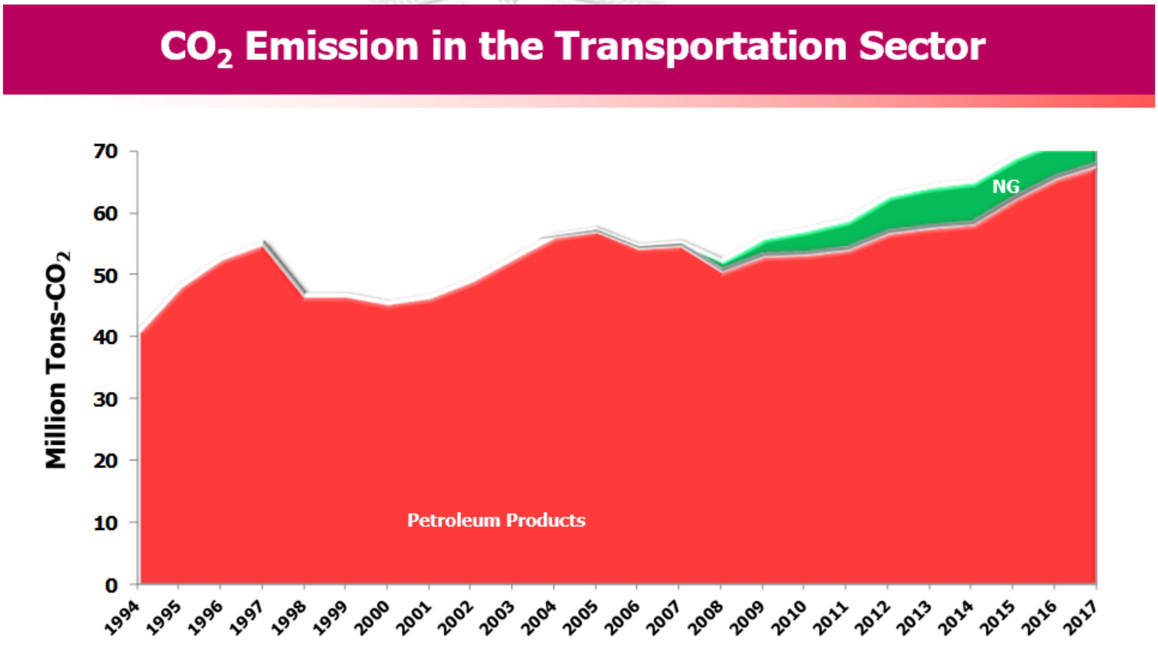


Figure 1 Number of vehicles registered in Bangkok from 2008 – 2018
Source: Adapted from Department of Transport (2018)

Bangkok has been suffering from terrible transport problems including traffic congestion, pollution, and parking problems. The long hours on the road people spend due to the congestion affect a country's social development, people's physical and mental health and cause considerable economic losses. Moreover, the heavy traffic leads to air pollution, including PM 2.5 particulates and greenhouse gases (GHG). Bangkok has been suffering from the smog that was reported to be "at-risk" or "unhealthy" levels air condition with the quantity of dangerous PM2.5 particulates leading to its air being given a code-red status (Air Quality and Noise Management Bureau, 2019). Besides, transportation is also a major cause of greenhouse gas emission, particularly carbon dioxide. Thailand's transportation and logistics sector releases approximately 26% of overall greenhouse emission behind the electricity generation sector and industrial sector accounting for 36% and 32%, respectively. Figure 2 shows that CO_2 emissions from the transportation sector in Thailand in the past 10 years have been increasing and this increase seems to be continuing (Energy Policy and Planning Office, 2019).



Unit: Million Tons-CO_2

Year	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Petroleum Products	40.94	48.21	52.71	55.24	46.77	46.92	45.58	46.55	49.25	53.02	56.5	57.41
NG									0.01	0.01	0.06	0.14
Year	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Petroleum Products	54.63	55.07	50.9	53.36	53.64	54.37	57.2	57.98	58.57	62.67	65.94	67.95
NG	0.23	0.5	1.65	3.03	3.85	4.9	5.92	6.52	6.73	6.46	5.92	4.74

Figure 2 CO_2 emission in the transportation sector in Thailand from 1994 to 2017
Source: Energy Policy and Planning Office (2019)

To reverse these negative trends of transport, many approaches have been implemented such as the development of an urban- train network, building more roads, and using alternative fuel vehicles. However, these solutions seem to have had no significant effect on the sustainability of Bangkok's transport system. However, car sharing is an emerging urban transportation option, which studies have shown contributes to a more effective transportation solution by cutting fixed costs associated with car ownership, reducing the number of vehicles on the road and lowering demand for parking space. Furthermore, car-sharing systems could reduce the consumption of physical and economic resources, as well as decrease environmental impacts (Baptista, Melo, & Rolim, 2014).

Impacts of car-sharing

Car-sharing services combine the advantages of both private and public transportation (Efthymiou & Antoniou, 2016). The impacts of car sharing can be divided into two main categories: impacts on environment and impacts on travel behavior.

1) Car-sharing impacts on the environment

Car sharing affects the environment in numerous ways. The most consistent finding of the past research found Green House Gases (GHG) impacts resulting from changes in travel behavior among car-sharing users. Firstly, car-sharing could reduce the number of owned private cars that bring the benefits to the environment in terms of decreased energy- consumption and GHG- emissions. Firnkorn and Müller (2011) examined the environmental effects of one- way (or free- floating) car-sharing systems in Ulm, Germany. The findings indicated that free- floating car-sharing systems lead to the reduction of owned private cars that results in a decrease in CO_2 emissions by 146-312 kg. per person annually. Baptista et al. (2014) estimated the car-sharing impacts on energy, the environment and mobility in Lisbon, Portugal. The result indicated that car-sharing systems could decrease physical and economic resource consumption, as well as decrease environmental impacts. In addition, if the shared cars shift to hybrid or electric vehicles, energy consumption can be reduced by 35% and 47% and CO_2 emission can be reduced by 35% and 65%, respectively. Another study found that car sharing could reduce car ownership by approximately 30% and car-sharing users drove lower about 15% to 20% than prior to joining the service (Nijland and van Meerkerk, 2017). Moreover, their study in the Netherlands showed that car sharing could replace the possession of a second or third private car. As a result, the emissions from car-sharing users decreased between 240 and 390 kilograms of CO_2 per person, per year, equivalent to between 13% and 18% of the CO_2 emissions related to car ownership and car use.

The environmental effects on car sharing in North America have been analyzed in numerous studies. Martin and Shaheen (2011) examined annual individual GHG emission from the members of car-sharing organization in North America. The results showed that car-sharing systems could reduce total GHG emission, even though most households joining car sharing increased their emissions by gaining access to vehicles, individual vehicle kilometers traveled (VKT) declined by 27%. Chen and Kockelman (2016) investigated the impacts of car-sharing life-cycle inventory on energy use and GHG emission in the United States. They found that people who join car-sharing systems reduced their average individual transportation energy use and GHG emissions by approximately 51%, a saving of around 5% of all household transport-related energy use and GHG emissions in the United States. Meanwhile, Clewlow (2016) compared travel behavior and vehicle ownership between car-sharing members and non-members in the San Francisco Bay area in the United States. The results indicated that in urban areas car-sharing members owned significantly fewer vehicles than non-members. Members owned 0.58 vehicles per household and non-members owned 0.96 vehicles per household. In suburban areas, car-sharing members drove significantly less than non-car-sharing members. Car-sharing member drove 15.8 vehicle miles per day and non-members 23.6 vehicle miles per day on average. The study also found that car-sharing members owned 18.3% of hybrid, plug-in hybrid or electric vehicles while only 10.2% of those vehicles owned by non-members.

Elsewhere, Jung and Koo (2018) analyzed the effects of car-sharing services on reduction on GHG emissions in South Korea. The findings indicated that the probability of using electronic-car-sharing vehicle increased when charging stations increased. This resulted in emission reduction.

2) Car-sharing impacts on travel behavior

Car sharing encourages alternative modes of travel including public transport, cycling and walking. These lifestyle lead to health improvements and reduced traffic congestion and demand for parking in urban areas (Shaheen, Mallery & Kingsley, 2012). The study of Mishra, Clewlow, Mokhtarian, and Widaman (2015) examined the impacts of car sharing on travel behavior in a San Francisco area. The results showed that car-sharing members were likely to walk, cycle and use transit more frequently than non-members. Clewlow (2016) found that 41.5% of car-sharing members took an automobile for their trip while 61.8% of non-members did. 34.9% of car-sharing members walked for their trip while only 23.0% of non-members did. Non-surprisingly, 8% of car-sharing members cycled for their trip while only 4 % of non-members did.

Car-sharing operation

As a model of car rental, car sharing is different from traditional car rental in these sense that of users typically rent cars for a short period of time and need to be a member of a car-sharing organization before using the shared car. The members can access a system any time via the internet and an application (Li, Liao, Timmermans, Huang, & Zhou, 2018).

Car sharing users can enjoy the privacy of car travel without the cost involved with car ownership. Customers only pay a registration fee, a monthly amount and a cost per distance unit driven (e.g. kilometer) or time spent using the service (Efthymiou & Antoniou, 2016). Car-sharing services can be categorized into two models as follows:

1) Trip model

- One-way or free-floating-car-sharing service: For this type of service, the car's pick-up and drop-off point can be different.

- Round trip: For this service, customers should return the car to the same station where they picked it up.

2) Ownership model

- Company: Both vehicles and system infrastructures are owned by a single company.

- Peer-to-peer: The infrastructures and systems may be provided by a company but vehicles are owned by users and shared among peers.

Typically, car-sharing members access the system through a mobile application that allows them to search the nearest drop point, car pick up or return location, as well as check a car's availability. The car should have its own telemetric system to communicate with the users as well as the control room at all times (J. Lee, Nah, Park, & Sugumaran, 2011). The users can use car sharing in five steps (Figure 3).

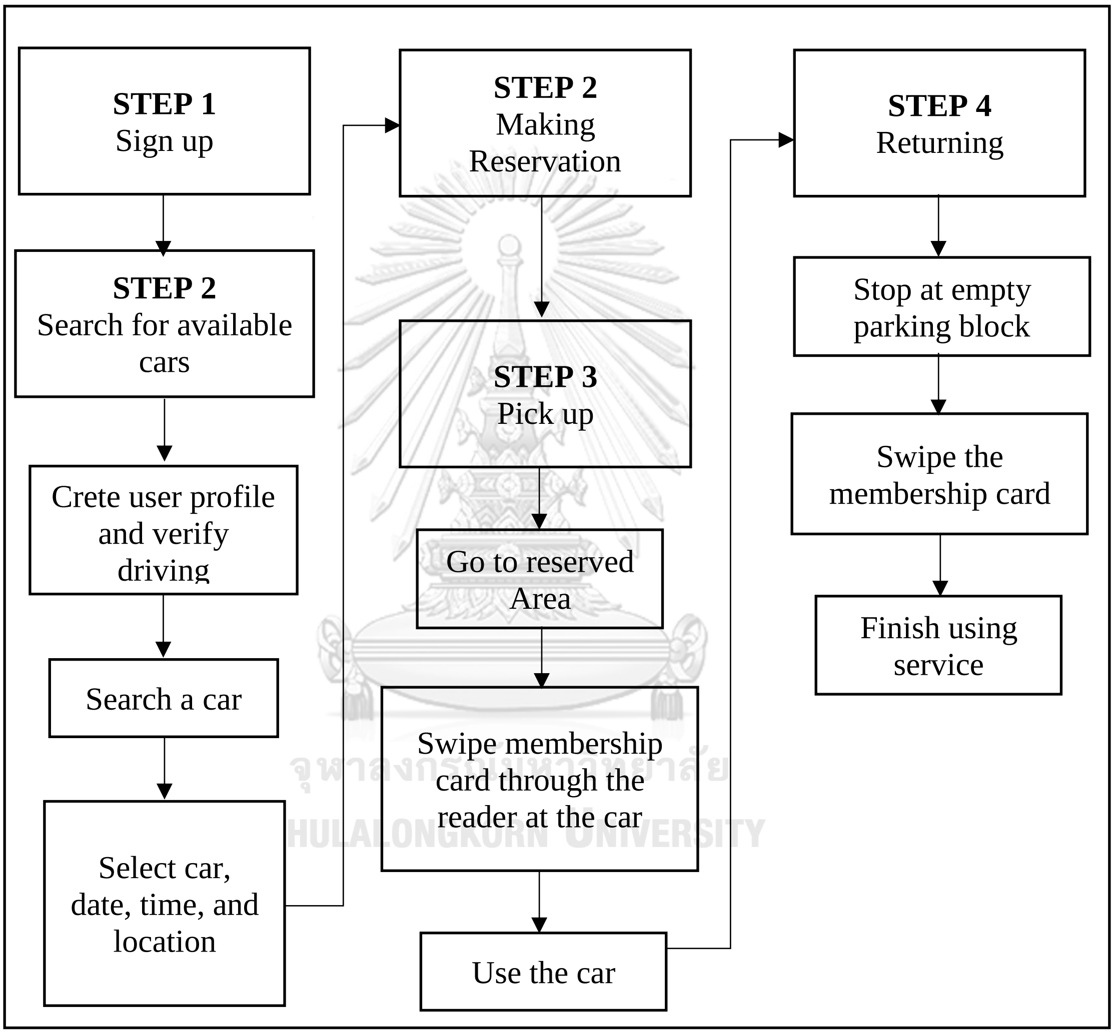


Figure 3 Steps for using car-sharing service
Source: Adapted from J. Lee et al. (2011)

1.2 Statement of problem

As car-sharing in Bangkok has been operated for just few years, many people are unaware of car sharing or may be uncomfortable in using a new transportation system. Many people are still using their private cars that caused many transportation problems. However, car-sharing is a new phenomenon in Bangkok that could solve transportation problems effectively and lead to a more sustainable urban transportation. It is important to estimate the current travel trends and understand customers' perception of the service in order to consider facility planning and capital investment. Therefore, this study will explore factors influence the probability of car-sharing adoption and customers' intention to use the service.

1.3 Research gap

Car-sharing studies are mainly in western countries (Catalano, Lo Casto, & Migliore, 2008; Coll, Vandersmissen, & Thériault, 2014; De Luca & Di Pace, 2014; El Zarwi, Vij, & Walker, 2017; Habib, Morency, Islam, & Grasset, 2012; Vinayak et al., 2018). Some studies have been carried out in east Asia such as China and Korea, but only few studies have investigated car sharing in south-east Asia (Fukuda, & Narupiti, 2005; Dissanayake & Morikawa, 2010).

The previous studies in North America, Europe, Australia and east Asia provide precious lessons for south-east Asia countries. However, this is of concern as conditions in south-east Asia are significantly different from other parts of the world because of local conditions vary to a lesser or greater extent, in terms of commuters' travel behavior, population density in urban areas, frequency of motor vehicle use, public transport structure and policies. Thus, further studies based in south-east Asia are needed, especially in Thailand where car-sharing service was just operated.

Moreover, previous studies separated demand estimation and customers' attitudes toward car sharing. However, the current research provided the factors influencing the use of car sharing with regard to both customers' profiles and attitudes.

1.4 Objectives

In order to understand the perception and intention of an individual towards car-sharing services, the objectives of this dissertation were set as follows;

1) To explore factors influencing the probability of using car-sharing services
2) To investigate customers' attitudes toward intention to use car-sharing services

1.5 Research questions

This dissertation comprised of two studies. The first phase of study attempted to forecast the demand for car sharing in Bangkok, as well as to explore the factors influencing the probability of using car-sharing services, based on customers' profiles and preferences. The second study explored the technology acceptance model of car sharing, related to customers' attitudes toward car sharing.

- *Study One*

This study focused on customer profiles and preferences in relation to on car-sharing adoption. The research question of Study One was:

To what extent do the demographic characteristics, travel behavior and car sharing preferences significantly affect the probability of using car sharing?

- *Study Two*

This study focused on customers' attitudes toward car sharing, based on an extension of the technology acceptance model (explored in 2.3) by adding four external variables: Personal Innovativeness, Environmental Concern, Social Influence and Perceived Risk. The research question of Study Two was:

Which factors have significant effects on customers' acceptance of car-sharing services?

1.6 Research scope

This research will focus on one-way car-sharing systems with company-owned shared cars and facilities. The area scope of this research is limited only in Bangkok.

1.7 Research contributions

As car sharing concept has been just introduced to the Bangkok metropolitan area for few years, it is importance to know what customers think about car sharing, the possibility of choosing this alternative travel mode, as well as the influencing factors which can contribute to the strategic planning of car-sharing organizations. On possible outcome of this research will be the development of an analytical tool which could predict the customers' decision on car sharing usage. The results will be helpful to car-sharing organizations that may wish to support the planners in the process of planning and decision making about the investment or policy measures that will best serve the public for sustainable urban transport development.

Chapter 2

Literature Review

This chapter will provide theoretical backgrounds and previous studies related to the travel choice decision model, factors influencing customers' intention to use car sharing and technology-acceptance theories. The sequence of this chapter is as follows:

2.1 Travel choice decision model

2.2 Factors influencing travel choice decision

2.3 Technology acceptance model

2.1 Travel choice decision model

Transportation is important for sustaining a country's economic development and fulfilling the individual travel need. Transport planning is crucial for future policies, goals, investment, and design. In the planning context, transportation forecasting aims to estimate the number of vehicles or people that will use a particular transport option in the future (Carey, 2018).

2.1.1 Four-step models

Transport modeling was initially developed in the United States during the 1950s, and then spread to the UK in the early 1960s (Khan, 2007). The classic transport model, namely the four-step model (FSM), has remained improving modeling techniques in specific sub-areas due to its overarching framework and logical appeal. The model is shown in Figure 4.

The model comprises four elementary stages which can be summarized as follows:

1) Trip generation

Trip generation estimates the frequency of travel origin or destination of a trip in each region of the study area by trip purpose, as a function of land uses and socio-demographics factors (Carey, 2018). Vitally, trip generation analysis shows total number of trips in each zone (Khan, 2007).

2) Trip distribution

Trip distribution provides a standard trip pattern of trip making by matching trip origins and destinations. The trip distribution model is necessary for a destination choice model and creates a trip table that summarized the number of trips generated between various zones (Khan, 2007).

3) Modal split

Modal split related to the choice of transport mode. Modal split or mode choice models refer to travel demand models (Khan, 2007). Mode choice determines the proportion of journeys between each origin and destination that are made using a certain mode (Carey, 2018). Mode choice is the most critical model in transportation planning, since it plays a vital role in making public transportation policy (de Dios Ortuzar and Willumsen, 2011).

4)Trip Assignment

Trip assignment refers to the process of allocating trip between an original location and destination through a certain mode to a route (Khan, 2007).

To this end, the decision of selecting the most appropriate mode of transport has been a major topic in travel behavioral modeling because it shows how individuals choose the most efficient travel mode available (Khan, 2007). Therefore, this thesis will focus on modal split or mode choice analysis, which is the third step of four step model, to investigate the effects of spatial attributes on car-sharing demand.

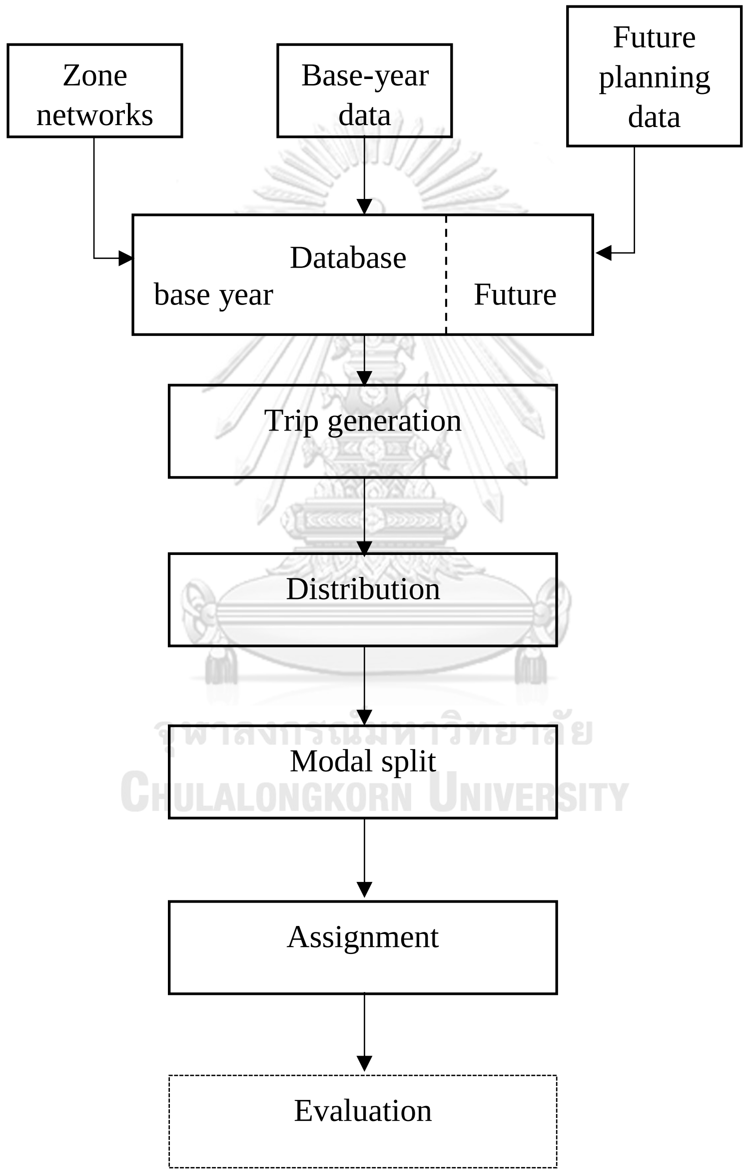


Figure 4 The classic four-stage transport model
Source: Adapted from de Dios Ortuzar and Willumsen (2011)

2.1.2 Discrete mode choice models

A mode choice model can be defined as one which captures an individual's decision-making process when confronted with various options (Khan, 2007). Transport modeling designs forecast travel behavior in a study area. When considering mode choice, the conventional mode choice models are discrete choice models (Beltman, 2014). Generally, discrete mode choice models assume that the probability of individuals who choose a particular opinion depends on their socioeconomic characteristics and the relative attractiveness of the opinion. The attractiveness of the alternatives can be represented by the concept of utility with theoretical summary defined as what the individual seeks to maximize (de Dios Ortuzar and Willumsen, 2011). Discrete choice modeling can be categorized into three main groups, namely logit models, probit models, and other choice models.

2.2.1 Logit Models

Logit models are often employed in the mode choice model because they are capable of modeling the complicated travel behaviors of any population with simple mathematical techniques. The theory of utility maximization has been used as the mathematical framework of logit models (Khan, 2007). Generally, logit models can be as binary, multinomial or nested logit models. The details of each can be explained as follows:

1) Binary Logit Model

The binary logit model is the simplest type of mode choice model. The choice of travel or the available alternatives are limited to two (Khan, 2007 and Carey, 2018). Figure 5 shows an example of a binary logit model, comparing private car and public transport.

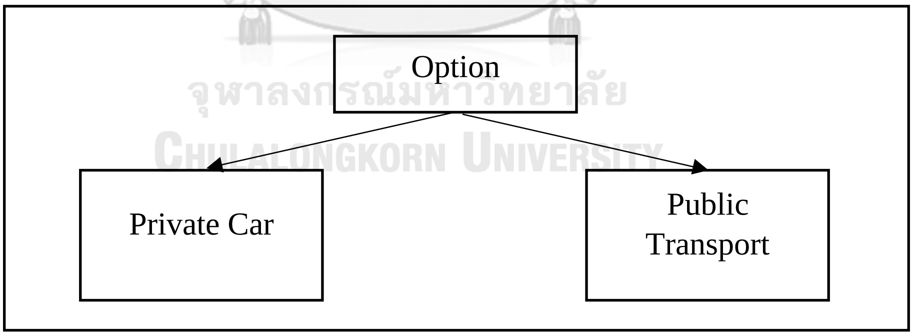


Figure 5 Example of a simple binary logit model
Source: Adapted from Khan (2007)

2) Multinomial Logit Model

The multinomial logit model assesses the likelihood of selecting the set of the available traveling alternatives in the choice set (Khan, 2007 and Carey, 2018). The simple multiple logit model is illustrated in Figure 6 with three set of alternatives: private car, bicycle and public transport.

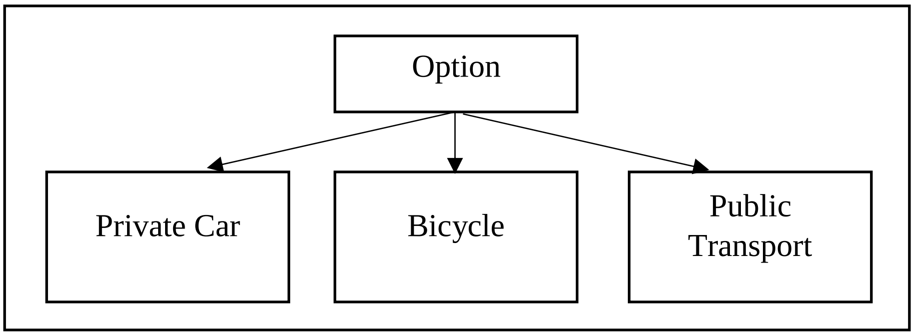


Figure 6 Example of a simple multinomial logit model
Source: Adapted from Khan (2007)

3) Nested Logit Models

The major limitation of simple logit models (binary or multinomial logit models) is they can be used only when the traveling alternatives in the choice set are unrelated to one another (independent). When groupings of more similar or connected modes exist, however, the assumption of an independent and equal error across all modes may not necessarily hold true (Khan, 2007; and Alraee, 2012).

By permitting correlation between the utilities and alternatives in common groups, a nested (hierarchical) logit model may be utilized to ease the limitations of a simple logit model. To develop a nested logit model, all the subsets of correlated alternatives are arranged into hierarchies or nests. Thus, each nest is represented by a composite alternative that competes with the others available to the individual (Khan, 2007; and Alraee, 2012). The nested logit model can be applied to both binary and multinomial logit models. Examples of a nested binary and multinomial logit models are presented in Figure 7 and Figure 8, respectively.

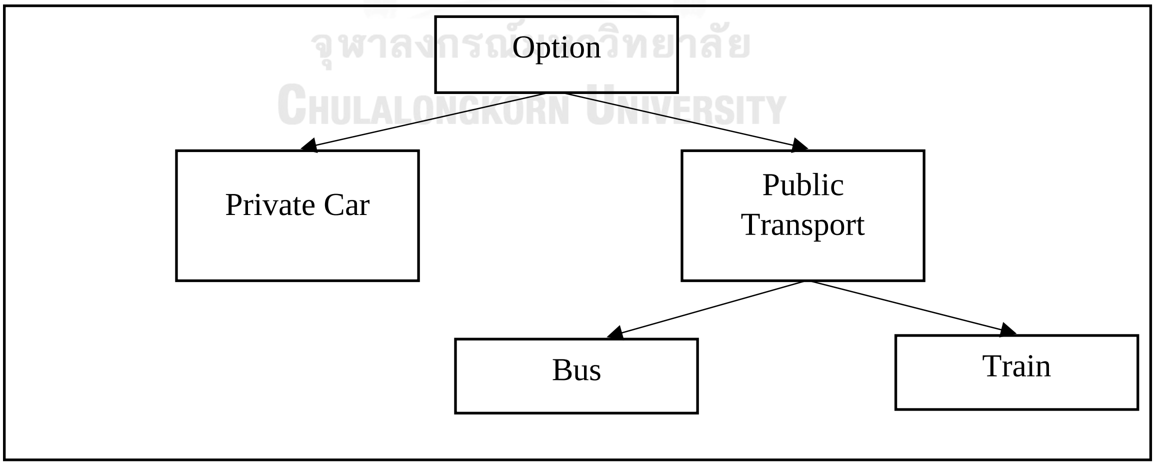


Figure 7 Example of a nested binary logit model
Source: Adapted from Khan (2007)

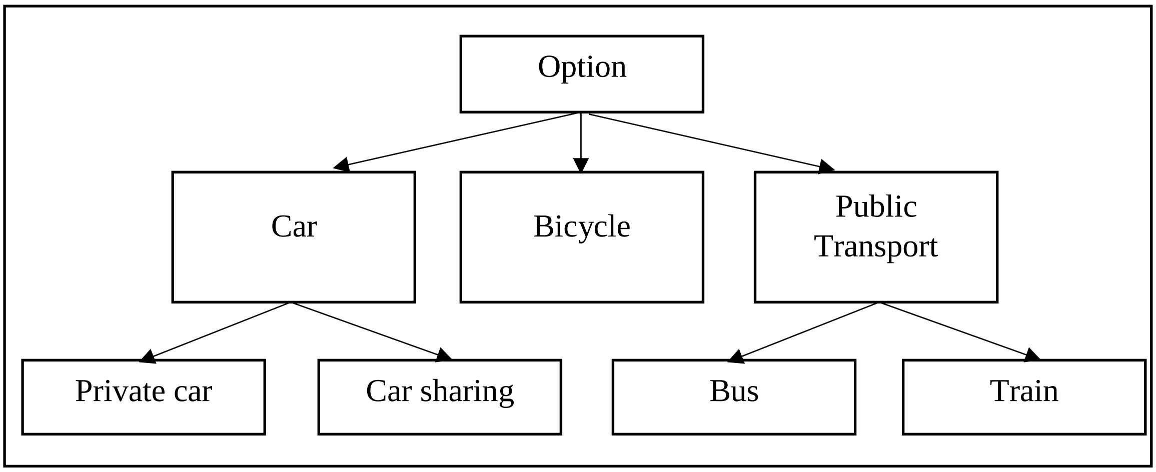


Figure 8 Example of a nested multinomial logit model
Source: Adapted from Khan (2007)

4) Mixed Logit Model

The Mixed Logit (ML) model can be derived under several behavior specifications (de Dios Ortuzar and Willumsen, 2011). The mixed logit model is estimated by various degrees of sophistication with mixtures of revealed preference and stated preference data (Hensher & Greene, 2001).

Several studies use a logit model approach toward car-sharing. For a simple binary logit model, modeled the propensity in adhering to car-sharing system regarding to user's behavior. To measure the propensity toward car-sharing, socio-economic and activity-related attributes along with satisfaction variables were utilized. Cartenì, Cascetta, and de Luca (2016) applied a binomial logit model framework to investigate and model the choice to switch from private car to car-sharing service, together with the probability of selecting an electronic vehicle in car-sharing services. In addition, ordered logit models can be used for capturing the probability of joining a car-sharing program. Efthymiou, Antoniou, and Waddell (2013) applied ordered logit models to measure the customers' propensity to join the vehicle sharing systems. Efthymiou and Antoniou (2016) estimated propensity to join car-sharing of young Greeks. They used a binary ordered logit model to determine individuals' propensity to join car-sharing services. A variety of variables were employed in the studies, in relation to socio-economic factors, travel characteristics and satisfaction with current travel patterns.

The multinomial logit model is widely used in mode choice transport and travel behavior, particularly in car-sharing service. Catalano et al. (2008) developed a demand model for anticipating the modal split of the urban transport demand in Palermo, Italy, by using multinomial logit (nested logit). The data obtained from the stated preference experiment with four different transport alternatives including private car, carpooling, car sharing, and public transport. Independent variables were socio-demographic characteristics such as sex, age, number of available cars, income. The main attributes were identified as trip travel time and cost and the number of cars per household. Dissanayake and Morikawa (2010) utilized a nested logit model for forecasting travel demand and household decision on owned private vehicle, mode choice and trip sharing.

Chevalier and Lantz (2015) proposed a multinomial logit model to investigate the mode choice of French households for their local daily trips as well as to estimate the potential shifts from private car to shared car. In addition, a conditional logit model was taken into account the economic rationality (cost and travel time) of individuals in their modal choices.

N. Wang and Yan (2016) used multinomial logistic regression to construct a model to capture customers' propensity to utilize electric car sharing (EVS). The socio-economic and travel characteristics were employed as independent variables and the choice willingness for EVS was the dependent variable.

Becker, Ciari, and Axhausen (2017) used a multinomial logit model to examine car-sharing use in Switzerland utilizing transaction data from a car-sharing operator in order to get a better understanding of the free-floating car sharing market. Dependent variables were mode choice including free-floating car-sharing, walking, bicycle, public transportation, taxi, and private car. Independent variables were socio-demographic characteristics. Attributes were trip information including cost, travel time, trip purpose, time of travel, group size, public transport service, original and destination of the trip, and weather.

Nevertheless, several papers employed mixed types of logit models to solve their research questions. Fukuda, Kashima, Fukuda, and Narupiti (2005) studied the possibilities of using car-sharing as a primary mode of travel and as a feeder mode of travel in Bangkok. The binary logit model was employed for feeder mode and the multinomial logit model was used for primary mode type system.

De Luca and Di Pace (2015) developed a model based on travel mode choice behaviors to estimate the effects of an inter-urban car-sharing program. They found that the results of Multinomial Logit (MNL) and Mixed Multinomial Logit (MMNL) model approaches were statistically significant. The model solutions were switching, unconditional switching and holding models. Independent variables were users' geographical location and socio-economic factors. The attributes included travel time, travel cost, access time, number of weekly car trips, number of weekly trips, origin of the trip and home-based trips.

Zoepf and Keith (2016) employed multinomial logit (MNL) and mixed logit (ML) forms to quantify the preferences of car-sharing users on vehicle types, namely gasoline, hybrid, plug-in hybrid, and electric vehicle. They performed a choice experiment with four attributes including price, access distance, and schedule.

Beria, Laurino, Maltese, Mariotti, and Boscacci (2017) investigated the likelihood of Milanese people subscribing to a peer-to-peer car sharing service. The characteristics of the people willing to join a car-sharing scheme were explored by the binomial logit model where the dependent variable was willingness to join the program. To investigate furth, a multinomial logit analysis was conducted using the following dependent variables: willingness to share with all members, willingness to share just with a limited number of known persons, or no willingness to share at all. The independent variables included socio-economic status, travel behavior and green attitude and policy.

2.2.2 Probit Models

Multinomial logit models may provide inaccurate forecasts in some circumstances, particularly when the utilities of some choice are correlated in a complex way. This problem happens when the attributes associated with one or more traveling alternatives are varied. However, probit model can be used in these cases to solve this problem (Khan, 2007). The primary distinction between the probit and logit model is that the cost function coefficients in the probit model are random (about normal distribution), while the logit model uses mean values.

Ordered probit model has been using in several car-sharing studies. D. Kim, Ko, and Park (2015) applied an ordered probit model to investigate factors affecting electronic vehicle sharing program participation in Seoul, Korea. The factors included 'shared vehicles', 'booking, fee and payment', 'renting, charging and driving', and 'social and economic perspective'. Dias et al. (2017) introduced a bivariate ordered probit model for predicting car-sharing and ride-sourcing service use. The study examined the effect of a variety of exogenous socioeconomic and demographic characteristics on the frequency with which those services were used. Vinayak et al. (2018) examined the impacts of socio-economic status, travel behavior, and latent factors on the frequency of utilizing shared mobility services using an ordered probit model.

Habib et al. (2012) developed an econometric model to forecast car-sharing users' behaviors in terms of membership duration, member decision to become active in a car sharing program, and monthly frequency usage of active members. Three components were included in the joint models: 1) a discrete temporal hazard model for membership length; 2) a binomial probit model for active or inactive membership; and 3) an ordered probit model for frequency of use.

Some studies have utilized a multivariate probit model. Becker et al. (2017) applied a multivariate probit approach to model the choice of four alternative forms of transport, namely car, car-sharing, season ticket, local season ticket. The model included socio-economic and attitude latent variables. Nazari, Noruzoliaee, and Mohammadian (2018) developed a model examining people's levels of interest in private and shared autonomous vehicles by employing multivariate ordered probit models.

2.2.3 Other choice models

In addition to logit and probit models, many researchers attempted to solve the restriction of the model limited by developing other choice models and paradigms. Firstly, hybrid choice models have been developed that take into account not just tangible attributes, but also intangible factors related to customers' perception and attitudes which are expressed through latent variables (de Dios Ortuzar and Willumsen, 2011).

Several studies applied a hybrid choice model (HCM) with a latent variable model into discrete choice model. The latent attitude model is used for measuring the relationship between latent variables and their observed variables. Simultaneously, the discrete choice model is used to estimate the impacts on the decision-making process of the latent variables and other observable variables associated with the choice alternative. J. Kim, S. Rasouli, and H. J. Timmermans (2017b) examined the role of social impact in uncertain car-sharing choices. They employed a hybrid choice model framework that is used for identifying social influence variables and their effects in a discrete choice analysis. J. Kim, S. Rasouli, and H. Timmermans (2017) studied the effects of uncertainty (due to non-availability of a shared car) and satisfaction with current transportation. A random regret-based minimization-based hybrid choice model was used for data analysis. The results found that both variables: uncertainty and satisfaction with current mobility options, significantly affected to the willingness to join car sharing. J. Kim, S. Rasouli, and H. J. Timmermans (2017a) used a hybrid decision modeling approach to investigate the impacts of activity-travel context and individual latent attitudes on intention to use car sharing under travel time uncertainty. The data collected were based on a stated choice experiment.

Coll et al. (2014) investigated the geographical location and socio-economics status which had potential effect to join car-sharing scheme. Zero-inflated negative binomial (ZINB) regression was adopted to model the spatial diffusion of car-sharing membership. The result showed that a 5D model, namely: density, diversity, design, distance to transit, and destination accessibility significantly influenced car-sharing membership.

El Zarwi et al. (2017) forecasted long-term travel patterns using a combination of discrete choice and technology adoption models. The model measured the impact of the new technology's spatial arrangement and sociodemographic factors on the adoption process, as well as calculated the impacts of social influences and level-of-service features on the new technology.

Besides discrete choice modeling, some researchers approached other techniques to develop a demand model for car-sharing. Seign, Schüßler, and Bogenberger (2015) developed a regression model to predict booking hot-spots for helping to determine business areas a-priori. Le Vine, Lee-Gosselin, Sivakumar, and Polak (2014) developed a new methodology for forecasting the market and implications of car-sharing systems, namely the Perceived Activity Set (PAS) conceptual framework. A summary of the used of demand model analysis is shown in Table 1.

Table 1 A summary of the used of demand model analysis

Author	Objectives	Approach					Noted
		Binary	Multinomial	Nested	Mixed	Other	
Fukuda et al. (2005)	To analyze the possibility of car-sharing application	✓					Logit
Catalano et al. (2008)	To develop demand model to forecast the modal split of the urban transport demand		✓				Logit
Dissanayake and Morikawa (2010)	To identify factors influencing car-sharing demand			✓			Logit
Habib et al. (2012)	To develop the model to forecast car-sharing membership duration	✓					Zero-inflated dynamic ordered probability model
Efthymiou et al. (2013)	To examine the factors affecting the adoption of vehicle sharing system by young driver	✓					Ordered Logit Model
Coll et al. (2014)	To analyze the geographical and socio-economic factors that favor membership of car-sharing					✓	Zero-inflated negative binomial (ZINB) regression
De Luca and Di Pace (2014)	To model the propensity of joining a car-sharing system	✓					Logit
Le Vine et al. (2014)	To predict the market of car-sharing					✓	Perceived Activity Set conceptual framework

Table 1 (continue)

Author	Objectives	Approach					Noted
		Binary	Multinomial	Nested	Mixed	Other	
Chevalier and Lantz (2015)	To explore the potential shift from personal car to shared car		✓				Logit
De Luca and Di Pace (2015)	To analyze the feasibility of an inter-urban car-sharing program		✓	✓	✓		Logit
D. Kim et al. (2015)	To explore the factors affecting the electronic vehicle sharing programs	✓					Ordered Probit Model
Seign et al. (2015)	To predict the inner-city booking hot-spots					✓	Regression
N. Wang and Yan (2016)	To explore consumers' use willingness of car-sharing		✓				Logit
Efthymiou and Antoniou (2016)	To examine the propensity to join car-sharing	✓					Ordered Logit Model
Zoepf and Keith (2016)	To quantify the preferences of car-sharing users on vehicle types		✓		✓		Logit
Cartenì et al. (2016)	To model the propensity to switch from private car to car sharing service	✓					Logit
J. Kim, S. Rasouli, et al. (2017b)	To investigate social influence in car-sharing decision					✓	Hybrid choice model

Table 1 (continue)

Author	Objectives	Approach					Noted
		Binary	Multinomial	Nested	Mixed	Other	
J. Kim, S. Rasouli, and H. Timmermans (2017)	To examine the effects of current mode satisfaction on car-sharing decision					✓	Hybrid choice model
J. Kim, S. Rasouli, et al. (2017a)	To investigate the relationship between individual latent attitudes and the intention to use car-sharing					✓	Hybrid choice model
Dias et al. (2017)	To understand the influence of soci- demographic variables on the frequency of using car sharing	✓					Ordered Probit Model
Becker, Loder, et al. (2017)	To model the use of free-floating car-sharing		✓				Logit
Becker, Ciari, et al. (2017)	To model the travel choice decision		✓				Probit
El Zarwi et al. (2017)	To forecast the adoption of car-sharing services		✓			✓	Latent Class Choice Model
Beria et al. (2017)	To identify the determinants to join peer-to-peer car-sharing		✓				Logit
Nazari et al. (2018)	To explore the propensity to use shares or private mobility		✓				Ordered Probit Model
Vinayak et al. (2018)	To model the usage levels of shared mobility	✓					Ordered Probit Model

2.3 Factors influencing travel choice decision

Based on previous studies, the factors influencing travel choice decision can be classified into four groups: individual characteristics, travel characteristics, car-sharing preference attributes and customers' attitude factors, as follows.

2.3.1 Personal factors

The numerous researchers have attempted to find the effects of socio-economic factors on the mode choice decision. However, there are still inconsistent conclusions. Research has shown that gender was a key factor in mode choice decisions. According to some research, males were more likely to join car-sharing scheme than females (Dissanayake and Morikawa, 2010; Cartenì et al., 2016; Wang and Yan, 2016; El Zarwi et al., 2017), while De Luca and Di Pace (2015); D. Kim et al. (2015); J. Kim, S. Rasouli, et al. (2017b); and Vinayak et al. (2018) found the reverse. However, De Luca and Di Pace (2014) and J. Kim, S. Rasouli, and H. Timmermans (2017) found that gender has no statistically significant effect on car-sharing decision.

The empirical studies found that age relatively affected the car-sharing adoption (Dissanayake and Morikawa, 2010; Coll et al., 2014 D. Kim et al., 2015; Dias et al., 2017; Kim, Rasouli and Timmermans, 2017; J. Kim, Rasouli and Timmermans, 2017; J. Kim, Rasouli and Timmermans, 2017b; Vinayak et al., 2018). Most of the studies claimed that younger adults tend to interested in car sharing. According to Wang and Yan (2016), those aged 18 to 30 were most receptive to car sharing, as well as Cartenì et al. (2016) discovered that persons under the age of 45 enhance their utility while switching from a private car to car-sharing service. De Luca and Di Pace (2015) found that people aged between 25-45 years old were more interested in car sharing. According to Fukuda et al. (2005), respondents in the age range of 36-55 years prefer car-sharing. On the other hand, Le Vine et al. (2014) found the minority of car-sharing users were predicted to be under age 40. Chevalier and Lantz (2015) found that the older the person, the great the opportunity to use a shared car. However, De Luca and Di Pace (2014) found that age did not have any effect on the choice to use a shared car.

The influence of income on the potential to use car sharing remains unclear. Some studies found that people who have high income are more willing to join car-sharing than others. Le Vine et al. (2014); J. Kim, S. Rasouli, et al. (2017b); El Zarwi et al. (2017) and Vinayak et al. (2018) all found that people who have high income are more willing to join car sharing than others. Fukuda et al. (2005) indicated that the target group of car sharing must be at least a middle-income group. In contrast, Efthymiou et al. (2013) and Efthymiou and Antoniou (2016) found that people who have medium to low income are more willing to join car-sharing. Dissanayake and Morikawa (2010); Coll et al. (2014); De Luca and Di Pace (2015); D. Kim et al. (2015) and Cartenì et al. (2016) all indicated that the higher a household's income, the lower the probability of using car sharing. Beaker, Loder, et al. (2017) found that the higher household income, the higher propensity to own a car. Dias et al. (2017) found that lower income individuals had a lower propensity to use car-sharing service. However, De Luca and Di Pace (2014) found no statistical significance related to income.

Several studies investigated the relationship between education and the use of car-sharing. Most of the findings were relatively certain that highly educated people are likely to join car-sharing services (Becker, Loder, et al., 2017; Dias et al., 2017; J. Kim, Rasouli and Timmermans, 2017; J. Kim, Rasouli and Timmermans, 2017b; Vinayak et al., 2018; Coll et al., 2014). However, Fukuda et al. (2005) found that people who have higher education were unlikely to be potential car-sharing users.

Employment status and occupation have significantly influenced the decision to use a shared car, according to Cartenì et al. (2016). Le Vine et al. (2014) and Efthymiou and Antoniou (2016) found that users of car sharing services were more likely to be employed status. Dias et al. (2017) found that people who are working full-time or are self-employed are more likely than other categories to use car-sharing services, since they may be utilizing the service for work-related activities. Similarly, Nazari et al. (2018) and Vinayak et al. (2018) found that full-time employees were more likely to choose car-sharing than self-employed persons do. In contrast, D. Kim et al. (2015) found that people interested in car-sharing were likely to be non-office workers or university students. In addition, Fukuda et al. (2005) found that government/state enterprise and company workers were more likely to use car sharing. Dissanayake and Morikawa (2010) found that commuters in the 'executive' job category had a negative preference for shared vehicle trips. Coll et al. (2014) found that the possibility of using car-sharing was associated with more central employment (civil service or head offices).

Family structure was also found to influence the travel mode choice decision. Those from larger households were likely to be more willing to join car-sharing schemes (Chevalier et al., 2015; J. Kim, Rasouli and Timmermans, 2017; Nazari et al., 2018). Meanwhile, Coll et al. (2014) found that car sharing is especially appealing to single-parent families with children while Dissanayake and Morikawa (2010) and J. Kim, S. Rasouli, and H. Timmermans (2017) found that families with children have a positive impact on household car ownership. On the other hand, Becker, Loder, et al. (2017) found that car-sharing membership is less likely for larger households.

Chevalier and Lantz (2015) found that marital status also affected the choice between personal and shared car. N. Wang and Yan (2016) found that married people are more willing to use car-sharing than unmarried people.

Many researchers found that the number of cars available in each household also affects mode choice decision. It is quite clear that car sharing is more appealing to people with no or low levels of motorization (Catalano et al., 2008; Coll et al., 2014; Chevalier et al., 2015; Dias et al., 2017; J. Kim, Rasouli and Timmermans, 2017; J. Kim, Rasouli & Timmermans, 2017b; Vinayak et al., 2018). Several studies found that the probability of using car sharing was decreased when people had their own car (De Luca et al., 2015; D.Kim et al., 2015; Cartenì et al., 2016; Efthymiou and Antoniou, 2016; Becker et al., 2017).

Some researchers also studied the relationship between population density and potential to join car-sharing services. Le Vine et al. (2014) and Dias et al. (2017) found that the people who live in area with higher residential density were more likely to use car sharing, while Coll et al. (2014) found non-significant effect of population density, but car sharing has good potential in medium-density suburbs. Chevalier and Lantz (2015) found that the lower density of the resident area, the higher numbers of private cars in households.

Other personal factors also affected the propensity to choose car-sharing. Fukuda et al. (2005) found a relationship between types of residents and the decision of using car-sharing. They found that people who live in their own house preferred to choose car sharing more than other groups. N. Wang and Yan (2016) studied monthly transportation expenditure. The results showed that with the increase of monthly transportation expenditure, more consumers prefer to choose car-sharing.

A summary of personal factors is shown in Table 2.

Table 2 A summary of personal factors

	Fukuda et al. (2005)	Catalano et al. (2008)	Dissanayake and Morikawa (2010)	Efthymiou et al. (2013)	Coll et al. (2014)	Le Vine et al. (2014)	Chevalier and Lantz (2015)	De Luca and Di Pace (2015)	D. Kim et al. (2015)	Carteni et al. (2016)
Gender			✓					✓	✓	✓
Age	✓		✓		✓	✓	✓	✓	✓	✓
Income	✓		✓	✓	✓	✓		✓	✓	✓
Education	✓				✓					
Occupation/Employment	✓		✓		✓	✓			✓	✓
Family structure			✓		✓		✓			✓
Marital status							✓			
Vehicle ownership		✓	✓		✓		✓	✓	✓	✓
Area density					✓	✓	✓			
Other personal factors	✓									

Table 2 (continue)

	Efthymiou and Antoniou (2016)	N. Wang and Yan (2016)	Becker, Loder, et al. (2017)	Dias et al. (2017)	El Zarwi et al. (2017)	J. Kim, S. Rasouli, et al. (2017b)	J. Kim, S. Rasouli, and H. Timmermans (2017)	Nazari et al. (2018)	Vinayak et al. (2018)
Gender		✓			✓	✓			✓
Age		✓		✓		✓	✓		✓
Income	✓		✓	✓	✓	✓			✓
Education			✓	✓		✓	✓		✓
Occupation/Employment	✓	✓		✓				✓	✓
Family structure			✓			✓	✓	✓	
Marital status		✓							
Vehicle ownership	✓		✓	✓		✓	✓		✓
Area density				✓					
Other personal factors		✓							

2.3.2 Travel characteristics

Trip characteristics also affect the mode choice decision. De Luca and Di Pace (2014) found the most significant factor that affected the propensity towards car-sharing systems was travel distance. Dissanayake and Morikawa (2010); Chevalier and Lantz (2015); and N. Wang and Yan (2016) found that the greater the distance traveled, the more likely it was that a private car would be chosen. This result consistent with De Luca and Di Pace (2014) who found long travel distance reduced the propensity to join car sharing system. Efthymiou et al. (2013) indicated that people who drove an average of 100-150 km. per day were the most willing to join a car-sharing program.

Moreover, trip frequency also plays a crucial role in mode choice decision. De Luca and Di Pace (2014), De Luca and Di Pace (2015) and Cartenì et al. (2016) found that people tend to drive their own car instead of a shared car if they have more trips per weekly.

For trip purposes, Efthymiou et al. (2013) found that people who normally use a taxi for trips related to their social activities tended to join car sharing. Cartenì et al. (2016) found that users who travel for business are less likely to convert to car-sharing. D. Kim et al. (2015) found that people tend to use car-sharing for leisure or personal purposes.

The findings of the relationship between current mode of travel and the intention to use car-sharing were relatively consistent. Efthymiou et al. (2013) found that car sharing is attractive to people who travel mainly by public transport such as bus, trolley or tram for their commute. This result was consistent with De Luca and Di Pace (2014) who indicated that commuters who traveled by bus were more likely to be interested in car sharing. Efthymiou and Antoniou (2016) found that commuters who travel by taxi are more willing to join car sharing. N. Wang and Yan (2016) found that people who usually take the subway, bus or bicycle are more willing to use car sharing.

Other factors affect the likelihood of using car sharing. J. Kim, S. Rasouli, et al. (2017a) found that time constraints have a negative and significant influence on the probability of using car sharing. Dissanayake and Morikawa (2010) found that people who travelled in Central Business District (CBD) prefer public transport or vehicle sharing rather than private car. De Luca and Di Pace (2015) indicated that home-based trips influenced the propensity to use a shared car.

Moreover, some external factors also impacted the travel mode decision. Becker, Loder et al. (2017) found that when it was raining and/or freezing at night, car-sharing becomes more appealing than public transport. However, it became less attractive when public transportation was frequently and densely served in the areas. Nazari et al. (2018) found that people who work night shifts were less likely to be interested in car-sharing. A summary of travel characteristic factors is shown in Table 3.

Table 3 A summary of travel characteristic factors

	Dissanayake and Morikawa (2010)	Efthymiou et al. (2013)	De Luca and Di Pace (2014)	Chevalier and Lantz (2015)	De Luca and Di Pace (2015)	D. Kim et al. (2015)	Carteni et al. (2016)	Efthymiou and Antoniou (2016)	N. Wang and Yan (2016)	J. Kim, S. Rasouli, et al. (2017a)	Nazari et al. (2018)
Travel distance	✓	✓	✓	✓					✓		
Trip frequency			✓		✓		✓				
Trip purposes		✓				✓	✓				
Mode of trip		✓	✓					✓	✓		
Time pressure										✓	
Trip area/origin	✓				✓						
Night									✓		✓
Weather									✓		

2.3.3 Car-sharing preference attributes

Many studies have found that travel cost and time have a strong bearing on the decision to use car sharing. (Catalano et al., 2008; Dissanayake & Morikawa, 2010; De Luca et al., 2015; Chevalier et al., 2015; Cartenì et al., 2016).

The probability of selecting car-sharing decreased when the cost variables of car sharing increased such as the deposit to join a car-sharing system, membership rate fees, and the hourly rate for using car sharing (Fukuda et al., 2005; Chevalier et al., 2015; J. Kim, Rasouli and Timmermans, 2017; J. Kim, Rasouli and Timmermans, 2017b). In addition, J. Kim, S. Rasouli, et al. (2017a) and Nazari et al. (2018) found that parking costs also affected the likelihood of using car sharing.

Time pressure has a negative and significant impact on the likelihood of using car sharing, according to Chevalier and Lantz (2015) and J. Kim, S. Rasouli, et al. (2017a). People would prefer car sharing if the access distance and waiting times were reduced (De Luca & Di Pace, 2015; J. Kim, S. Rasouli, et al., 2017a). Fukuda et al. (2005) found that people were willing to wait a maximum of approximately 15-20 minutes for a shared car, with an access time of approximately 5-7 minutes. J. Kim, S. Rasouli, et al. (2017a) found that the likelihood of adopting car-sharing is often more elastic in terms of wait time than it is in terms of access time and travel time variance.

Car-sharing parking location is also an important factor in the car-sharing decision (De Luca et al., 2015; Nazari et al., 2018). According to Nazari et al. (2018), walking distance from car-sharing parking location to/from the work place also impacted on the decision to use a shared car. El Zarwi et al. (2017) found that the most effective way to boost the number of adopters was to locate a new car-sharing station outside a large technological company. The distance of car-sharing parking to a transit bus also influenced the decision to use car sharing. Coll et al. (2014) found that when car-sharing stations were located within the first 250 meters of each other, the likelihood of using car sharing increases by 53% and by 25% between 250 and 500 meters. However, Becker, Loder et al. (2017) found that the distance between car-sharing stations has no significant effect on the likelihood of participation in a car-sharing program.

The availability of shared cars is an essential factor in a car-sharing decision (J. Kim, S. Rasouli, & H. Timmermans, 2017). Li et al. (2018) found that fleet size and vehicle distribution also significantly influenced the choice of shared car and activity-travel pattern. In addition, the level of service attributes influenced the penetration of the car-sharing market (De Luca & Di Pace, 2014).

Crucially, an awareness of car sharing is needed for increasing the probability of choosing car-sharing service (Dias et al., 2017). Likewise, De Luca and Di Pace (2014) indicated that car-sharing demand was influenced by an individual's degree of familiarity with the service. A summary of car-sharing attribute factors is shown in Table 4.

Table 4 A summary of car-sharing preference attributes

	Fukuda et al. (2005)	Catalano et al. (2008)	Dissanayake and Morikawa (2010)	Coll et al. (2014)	De Luca and Di Pace (2014)	Chevalier and Lantz (2015)	De Luca and Di Pace (2015)	Carteni et al. (2016)	N. Wang and Yan (2016)	Becker, Loder, et al. (2017)	Dias et al. (2017)	El Zarwi et al. (2017)	J. Kim, S. Rasouli, et al. (2017b)	J. Kim, S. Rasouli, and H. Timmermans (2017)	J. Kim, S. Rasouli, et al. (2017a)	Li et al. (2018)	Nazari et al. (2018)
Cost	✓	✓	✓			✓	✓	✓	✓				✓	✓			✓
Time	✓	✓	✓			✓	✓	✓							✓		
Station location				✓			✓			✓		✓					✓
Vehicle availability														✓		✓	
Level of service					✓												
Aware of car-sharing					✓						✓						

2.3.4 Customers' attitudes

Several studies found that customers' attitudes influenced travel mode choice decision including individual attitude, travel habits, experiences, social norms, and technology familiarity. Diana (2010) suggest that cognitive attitude is a crucial element in determining the propensity to switch mode. Some studies found that the users of car-sharing tend to be environmentally conscious with a "green" travel behavior (Coll et al., 2014; Efthymiou and Antoniou, 2016; J. Kim, S. Rasouli, and H. Timmermans (2017); Nazari et al., 2018). However, Efthymiou et al. (2013) found that people who are the most environmentally conscious tend to join bike-sharing rather than car-sharing schemes.

Travel habits are an important attribute in the decision of choosing travel mode choice. Diana (2010) indicated that car sharing will be more successful with customers with more multimodal behaviors. J. Kim, S. Rasouli, et al. (2017a) found that the people who seek privacy while traveling tend to prefer their private car and shared car compared with public transport.

The experiences of the current travelling mode are also crucial for the propensity of choosing car sharing. The studies of Dissanayake & Morikawa (2010); Efthymiou et al. (2013); De Luca & Di Pace (2014); J. Kim, S. Rasouli, et al. (2017b) and J. Kim, Rasouli and H. Timmermans (2017) found that satisfaction with present modes of transportation, such as dependability and comfort, positively affected to the likelihood of joining a car-sharing program. J. Kim, S. Rasouli, et al. (2017b) found that people who are content with their current use of public transport are more likely to join a car-sharing system than to purchase a second vehicle. However, Efthymiou and Antoniou (2016) found that the more pleased individuals are with their present mode of transportation, the less likely they are to join a car-sharing plan.

Social influence is another important factor in travel mode choice decision. D. Kim et al. (2015); El Zarwi et al. (2017) and Vinayak et al. (2018) found social influences and network effect have a positive impact on car-sharing adoption. While, J. Kim, S. Rasouli, et al. (2017b) found that people are likely to join car-sharing service when more family members and friends joined.

The familiarity of internet and online operation have been found the association with the potential to join car-sharing program (Coll et al., 2014). El Zarwi et al. (2017) also found that people used to new technology adoption are more likely to adopt car-sharing services.

A summary of customers' attitude factors is shown in Table 5.

Table 5 A summary of customers' attitude factors

	Diana (2010)	Dissanayake and Morikawa (2010)	Efthymiou et al. (2013)	Coll et al. (2014)	De Luca and Di Pace (2014)	D. Kim et al. (2015)	Efthymiou and Antoniou (2016)	El Zarwi et al. (2017)	J. Kim, S. Rasouli, et al. (2017b)	J. Kim, S. Rasouli, and H. Timmermans (2017)	J. Kim, S. Rasouli, et al. (2017a)	Nazari et al. (2018)	Vinayak et al. (2018)
Cognitive attitude	✓												
Environmentally concern			✓	✓			✓				✓	✓	
Cost sensitiveness											✓		
Multimodal behaviors	✓												
Privacy seeking											✓		
Satisfaction of current mode		✓	✓		✓		✓		✓	✓			
Social influence						✓		✓	✓				✓
Familiarity of internet and online operation				✓									
New technology adoption								✓					

2.4 Technology Acceptance Model (TAM)

The previous section explored the literature on customers' profile, travel characteristics, car-sharing preference together with customers' attitude factors influenced travel mode choice decision. However, when considering deeply about customers' attitude, there are many theories and previous studies explaining about a new technology acceptance. Thus, this section will address the mechanisms of the attitudes of the customers toward car sharing.

There are several theoretical frameworks describing the customers' intention for adopting new technology such as theory of reason action (TRA), theory of planned behavior (TPB) and the technology acceptance model (TAM).

The current study employed an extension of TAM to examine the attributes influencing customers' acceptance of car-sharing services. There are several reasons for selecting TAM in this study. Firstly, TAM is commonly used as a model for predicting technology adoption, including car-sharing services (J. Kim, S. Rasouli, & H. Timmermans, 2017; Y. Lee, Kozar, & Larsen, 2003; Liu & Yang, 2018; Müller, 2019; Schlüter & Weyer, 2019; Wan et al., 2016; Y. Wang, Wang, Wang, Wei, & Wang, 2020). Moreover, TAM has been found to have greater explanatory power than other models, such as TRA and TPB (X.-S. Lu, Liu, & Huang, 2015). Mathieson (1991) compared the predictive performance of the TAM and TPB models. The results revealed that both models accurately predicted intention to use, although TAM performed somewhat better empirically.

2.4.1 Evolution of the Technology Acceptance Model

The technology acceptance model (TAM) was initially developed by Davis (1985) based on the theory of reasoned action (TRA) and the theory of planned behavior (TPB) (Müller, 2019). The TAM is widely used to forecast the adoption of developing technologies, since it is a practical method for determining the incentive to use the system (Lang, 2019).

TRA was established by Fishbein and Ajzen (1975) to explain the psychological basis for an individual's intention to engage in conscious actions. The TRA combines two main factors for explaining an intention: (1) attitude towards the behavior; and (2) subjective norm (Barnes & Mattsson, 2017), as illustrated in Figure 9.

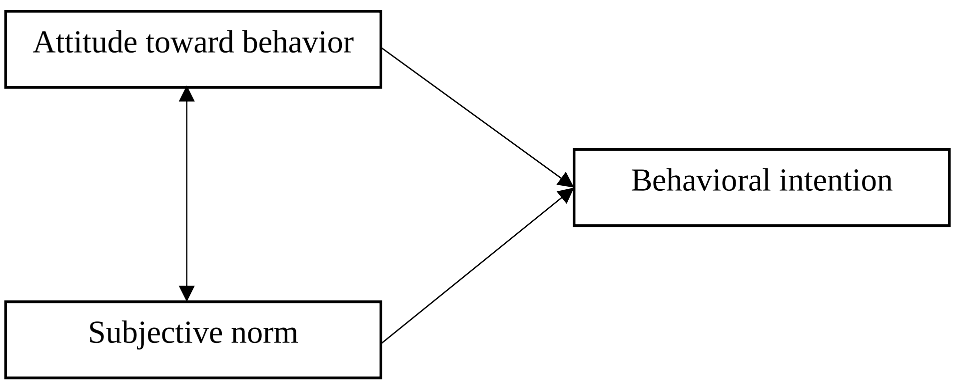


Figure 9 Theory of reason action (TRA)

Source. Adapted from Fishbein and Ajzen (1975)

Ajzen and Fishbein (1980) cited in Chua, Chiu & Chiu (2020) reconstructed the TRA by extending more variables, namely perceived behavioral control, and entitled “The theory of planned behavior (TPB)”. According to Jing, Huang, Ran, Zhan, and Shi (2019), perceived behavioral control defines as the perceived ease or difficulty of a particular behavior performance. The TPB model indicated that human behavioral intention is influenced by three main factors: attitude toward behavior, subjective norm, and perceived behavioral control, as illustrated in Figure 10.

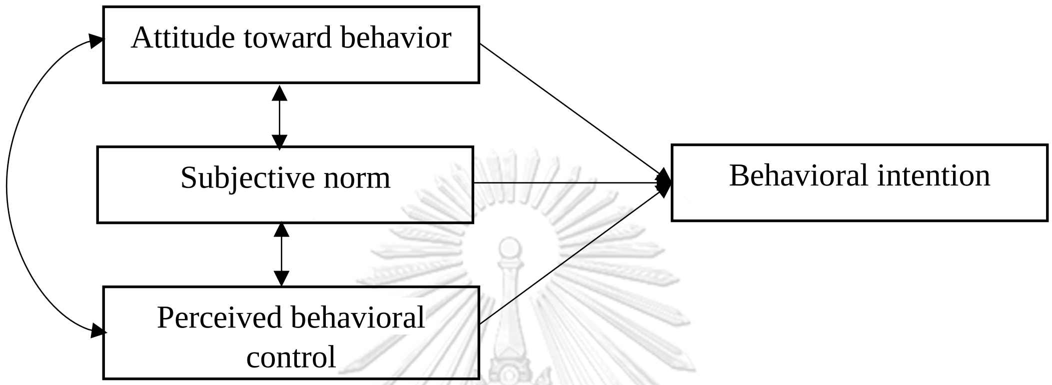


Figure 10 The theory of planned behavior (TPB)
Source. Adapted from Chua et al. (2020)

Davis (1985) developed “The Technology Acceptance Model (TAM)” by adopting the TRA and TPB framework. The TAM further added two indicators namely: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) to describe an individual’s acceptance of information systems (Davis, 1985). Originally, PU referred to the extent to which an individual believes that adopting a certain system would enhance his or her work performance (Y. Lee et al., 2003). In addition, the PEOU refers to the degree to which an individual feels that using a particular system will be effortless (Davis, 1985). In TAM, the PU and PEOU influence the attitude toward using, and attitude affects the actual system use of the new technology. The original model of TAM is shown in Figure 11.

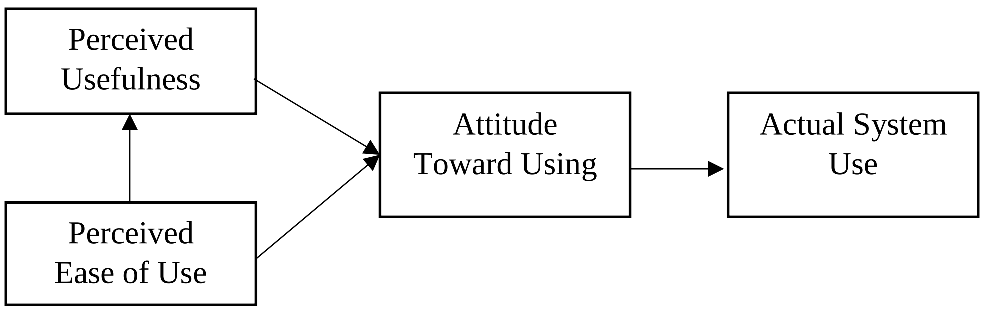


Figure 11 Technology Acceptance Model
Source: Davis (1989)

2.4.2 Model Developments and Extensions

After introducing the TAM, many researchers attempted to validate and develop the model in different technologies, situations and tasks to confirm TAM as an accurate tool for measuring user acceptance behavior.

When the validation was confirmed, the expansion of the model with new variables began to investigate the relationship between the major TAM constructs and antecedents (or external) variables in an effort to explore boundary conditions (Y. Lee et al., 2003). The model of extension of TAM is shown in Figure 12.

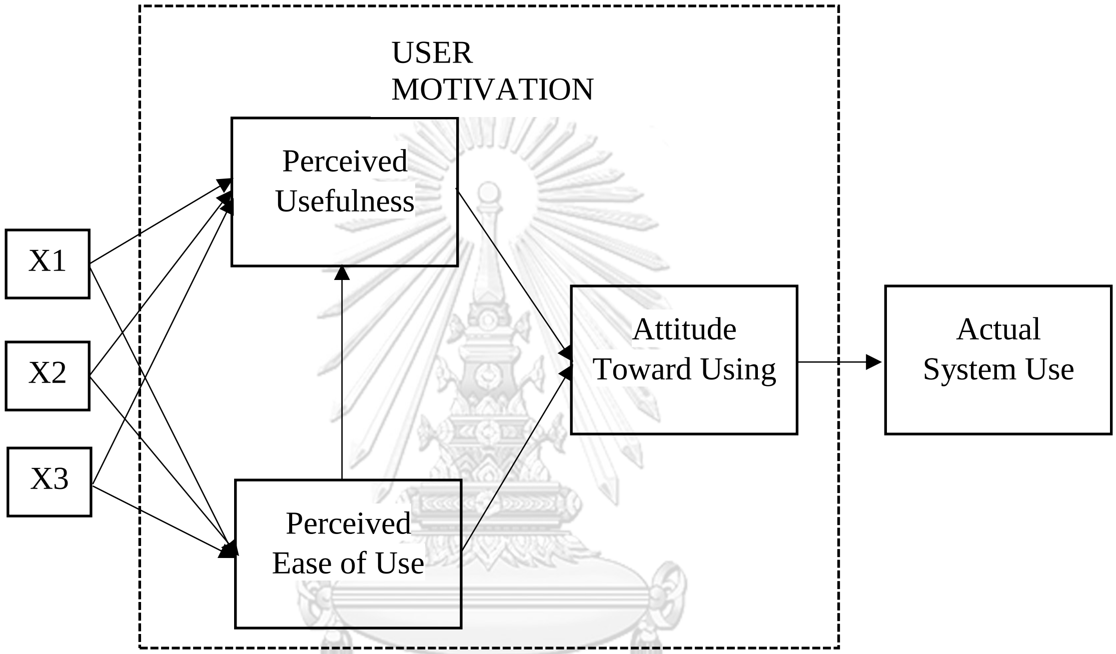


Figure 12 The extension of Technology Acceptance Model
Source: Adapted from Chuttur (2009)

The unified theory of acceptance and use of technology (UTAUT), established by Venkatesh, Morris, Davis, and Davis (2003), is one of an extension of the technology acceptance model (TAM). In comparison to TAM, UTAUT incorporates two additional variables: social influences and facilitating conditions. Social influences refer to people's belief that they can utilize new technologies while adhering to their social group's norms and projecting a favorable picture of themselves. Meanwhile, facilitating conditions are defined as the extent to which people believe they are giving with favorable context and the resources necessary to utilize the system (Fleury, Tom, Jamet, & Colas-Maheux, 2017). In addition, UTAUT contained the moderating factors including the individuals’ feature and their prior experience, particularly, their age, sex, experience, and voluntariness of use. The model is demonstrated in Figure 13.

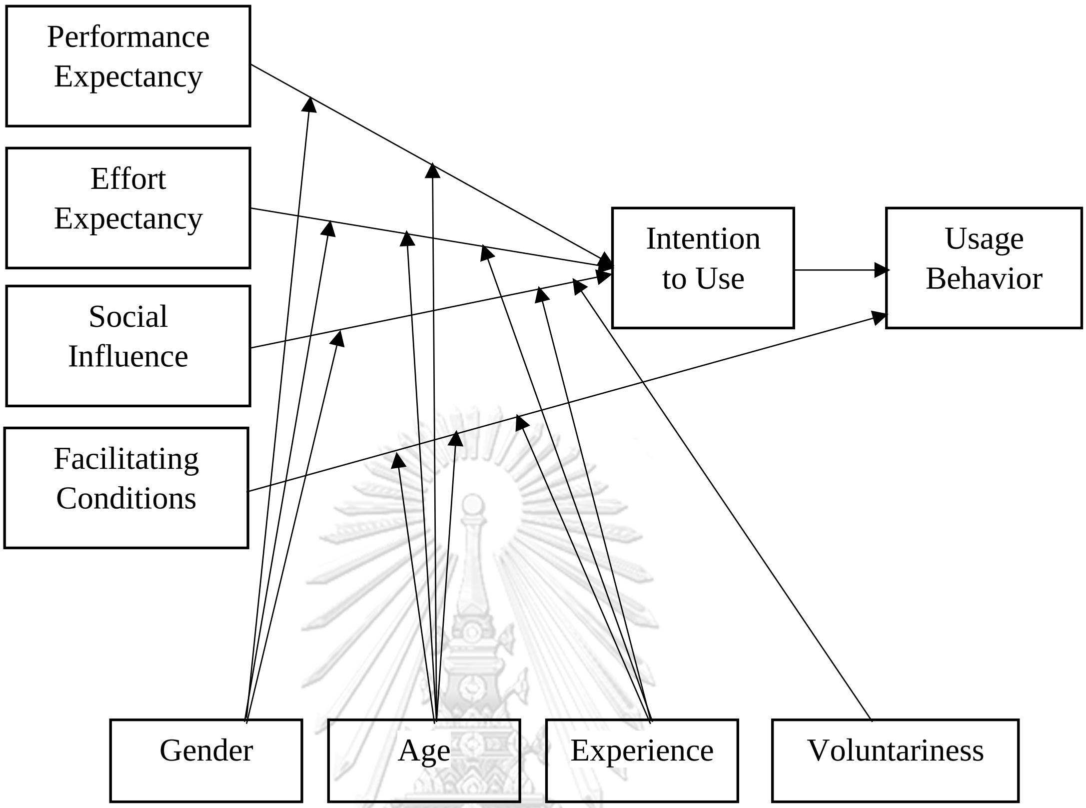


Figure 13 Unified Theory of Acceptance and Use of Technology (UTAUT)
Source: Venkatesh et al. (2003)

However, many researchers attempted to develop and extend the TAM for further understanding, as well as applied the theoretical model in various fields including information systems, hospital information systems, marketing technology, and transportation. Thus, the relationship of the constructs within the TAM have been confirmed for a variety of technologies (Müller, 2019). In sharing economy and transport research, particularly in car-sharing services, several studies have also used the TAM framework to explore the factors affecting the intention to use the service. Various studies have investigated the behavioral intention with extended variables, as follows.

Lamberton and Rose (2012) studied the factors affecting the propensity to participate in a commercial sharing system. The results showed that sharing organization can use perceptions of personal and sharing partners' usage patterns to affect risk perception and subsequent propensity to participate in a commercial sharing system.

Barnes and Mattsson (2017) created a model to explain consumer outcomes for collaborative consumption. Their findings indicated that factors influencing consumers' intentions to adopt car-sharing include perceived economic, environmental and social advantages, as well as perceived utility and pleasure. They did not, however, discover an impact of social impact on use intention.

Dall Pizzol, Ordovás de Almeida, and do Couto Soares (2017) proposed a scale to measure the motivators, facilitators and constraints for collaborative consumption of car-sharing in Brazil. Their model comprised of six dimensions, including cost saving, convenience, socio-environmental consciousness, belief in the common good, social identity, trust and risks.

Giang, Trang, and Yen (2017) examined the factors influencing the intention to adopt ride sharing applications in Vietnam. They employed the TAM and TPB for their research framework. Thus, the variables from both TAM and TPB framework included perceived usefulness, perceived ease of use, attitude towards the applications, subjective norms, perceived behavioral control, and intention to use the applications.

H. Kim, Choi, Kim, and Park (2017) investigated the motivation factors towards car-sharing services on the basis of the TAM model. Their findings indicated that perceived reliability, compatibility, enjoyment of car-sharing service and innovative tendencies have a positive effect on the intention to use car sharing. However, the researchers did not find the effects of perceived concern and perceived cost of using the service on the adoption of car-sharing services.

Liu and Yang (2018) examined users' adoption of a sharing economy with the TAM framework, together with herd behavior which involved subjective norm and imitating others. The result indicated that perceived usefulness and perceived ease of use are the main factors influencing behavioral intention. They also found that trust was a mediator of subjective norm and perceived ease of use. In addition, imitating others affects behavioral intention.

Oyedele and Simpson (2018) evaluated the effects of sharing utilities on intention to use sharing services in three different contexts: car-sharing, room-sharing, and household good purchases. The finding indicated that flexibility utility had the strongest direct effect on the intention to use sharing consumption.

Jing et al. (2019) explored the factors affecting mode choice intention. The results indicated that the primary barriers to passengers using shared autonomous vehicles were the lack of understanding about the technology and perceived risk. However, the most critical factor determining the intention to use the service was subjective norm.

Mattia, Mugion, and Principato (2019) employed the TPB framework with additional variables to examine the intention to re-use free-floating car-sharing. The results revealed that economic, environmental and social benefits indicate the attitude towards free-floating car-sharing and that attitude, perceived behavioral control, and subjective norm have a significant on the future intention to re-use the service.

Mensah, Tianyu, Zeng, and Chuanyong (2019) examined the factors determining the continued intention to use car-sharing in China. According to the unified theory of acceptance and use technology (UTAUT), performance expectancy, reliability, efficiency, security and privacy were all important predictors of continued intention to use the service. Effort expectancy, on the other hand, was not a significant factor.

Müller (2019) adopted the TAM framework to compare customer acceptance of three automotive technologies: autonomous driving, electric power train and car sharing. The results confirmed the relationship of the constructs within the TAM model with other four external constructs: perceived enjoyment, objective usability, attitude towards environmental protection, and innovativeness.

Schlüter and Weyer (2019) employed the TAM model with five additional predictors of electronic vehicle car-sharing acceptance, namely mobility, car ownership, urbanity, ecological awareness, and technophilia. The results revealed that generally car-sharing acceptance was increased by urbanity, ecological awareness, technophilia and car-sharing experience.

Claasen (2020) developed a framework based on the UTAUT and TPB to investigate the factors affecting the intention to use shared modes and intention to reduce household car ownership. The results revealed that demographic and travel characteristics, attitude and social norm influence the intention to use shared modes.

Hjorteset and Böcker (2020) examined the interest, intention and decision to enroll in a car-sharing program in Norway. Socio-demographic factors, the environment, personal traits and car ownership were investigated in relation to the willingness to use car sharing. The findings showed that car-ownership and environmental concerns affected the adoption of car sharing.

Ibrahim, Borhan, and Rahmat (2020) examined the factors influencing the intention to use Park-and-Ride (P&R) facilities in Malaysia. The TPB framework with trust as an extended variable was applied to their work. The results found that attitude, subject norm, and perceived behavioral control (PBC) have a strong positive influence on the intention to use the service. Moreover, trust also has indirect significant effects on user intention to use P&R facilities through attitude and PBC.

Y. Wang et al. (2020) developed ride-sharing acceptance model based on the TAM with three extension variables: personal innovativeness, environmental awareness and perceived risk. The results revealed that personal innovativeness, environmental awareness and perceived usefulness have made people more likely to use ride-sharing services. On the other hand, perceived risk negatively influenced perceived usefulness and intention to use ride-sharing services.

A summary of external variables of technology acceptance models from previous studies of car-sharing services and other related services is shown in Table 6.

Table 6 A summary of external variables of acceptance models from previous studies

Reference	Barnes & Mattsson (2017)	Fleury et al. (2017)	Kim et al. (2017)	Mattia et al. (2019)	Mensah et al. (2019)	Müller (2019)	Schlüter & Weyer (2019)	Claasen (2020)	Hjorteset & Böcker (2020)
Framework	Other	UTAUT	TAM	TPB	UTAUT	TAM	TAM	UTAUT	Other
Area	Carsharing	Carsharing	Carsharing	Carsharing	Carsharing	Carsharing	Carsharing	Carsharing	carsharing
Intention	✓	✓	✓	✓	✓	✓	✓	✓	✓
Attitude			✓	✓		✓		✓	
Subject Norms				✓					
Perceived behavioral control				✓					
Perceived Usefulness	✓		✓			✓	✓		
Perceived Ease of use						✓	✓		
Performance expectancy		✓			✓			✓	
Effort expectancy		✓			✓			✓	
Facilitating conditions		✓							
Social influence	✓	✓		✓				✓	✓
Sociodemographic								✓	
Environmental aspects	✓	✓		✓		✓	✓		✓
Economic benefits	✓		✓	✓					✓
Perceived Risk					✓				
Trust	✓								
Security/Privacy			✓		✓				
Reliability			✓		✓				
Efficiency					✓				
Experience							✓		
Car owner							✓		✓
Multimodality							✓		
Compatibility			✓						
Urbanity							✓		
Innovativeness			✓			✓	✓		
Perceived enjoyment	✓		✓			✓			
Object Usability						✓			
Social benefits	✓								

Table 6 (Continue)

Reference	Lee et al. (2003)	Lamberton & Rose (2012)	Wan et al. (2016)	Dall Pizzol et al. (2017))	Liu & Yang (2018)	Oyedele (2018)	Jing et al. (2019)	Kim et al. (2019)	Chua, Chiu & Chiu (2020)	Ibrahim et al. (2020)	Wang et al. (2020)
Framework	TAM	ABC	TAM	ABC	TAM	ABC	TPB	TAM	TRA	TPB	TAM
Area	Ridesharing	Commercial sharing	Uber	collaborative consumption	Sharing economy	Sharing utility (include cs)	Share AV	On-demand	AirBnB	Park & Ride	Ridesharing
Intention	✓	✓	✓		✓	✓	✓	✓		✓	✓
Attitude	✓						✓	✓		✓	
Subject Norms	✓				✓		✓			✓	
Perceived behavioral control	✓						✓			✓	
Perceived Usefulness	✓				✓			✓			✓
Perceived Ease of use	✓				✓			✓	✓		✓
Social influence				✓		✓			✓		
Environmental aspects				✓							✓
Economic benefits			✓	✓		✓					
Perceived Risk		✓		✓			✓	✓			✓
Trust				✓	✓	✓			✓	✓	
Security/Privacy									✓		
Reputation									✓		
Perceived safety			✓					✓			
Relative flexibility						✓					
Convenience			✓	✓					✓		
Accessibility			✓								
Shareaids						✓					
Knowledge							✓				
Compatibility								✓			
Relative advantage								✓			
Innovativeness											✓
Imitating other					✓						
Familiarity		✓				✓					
Moral utility						✓					
Belief in the common good		✓									

Note: ABC = Access-based consumption model

Chapter 3

Methodology

The previous chapter explored the prior literature regarding travel choice decision model, factors influencing travel choice decision and the technology acceptance model. In this chapter, will start with the development of conceptual framework and hypotheses. Then, research methodology will be described. The structure of this chapter is as follows.

3.1 Conceptual framework and hypotheses

3.1.1 Conceptual framework of Study One

3.1.2 Hypothesis Development and conceptual framework of Study Two

3.2 Overall research design

3.3 Research methodology of Study One

3.3.1 Area of study

3.3.2 Stated preference methods

3.3.3 Questionnaire design

3.3.4 Population and sample

3.3.5 Data collection method

3.3.6 Data analysis

3.4 Research methodology of Study Two

3.4.1 Survey Research Methodology

3.4.2 Questionnaire Design

3.4.3 Population and Sample

3.4.4 Data collection method

3.4.5 Analysis Technique

3.1 Conceptual framework and hypotheses

3.1.1 Conceptual framework of Study One

In Study One, users' characteristics and preferences including socio-economic status, travel behavior, car-sharing awareness and experience, and car-sharing preference attributes were evaluated to examine the intention to use car sharing. The conceptual framework of the Study One is presented in Figure 14.

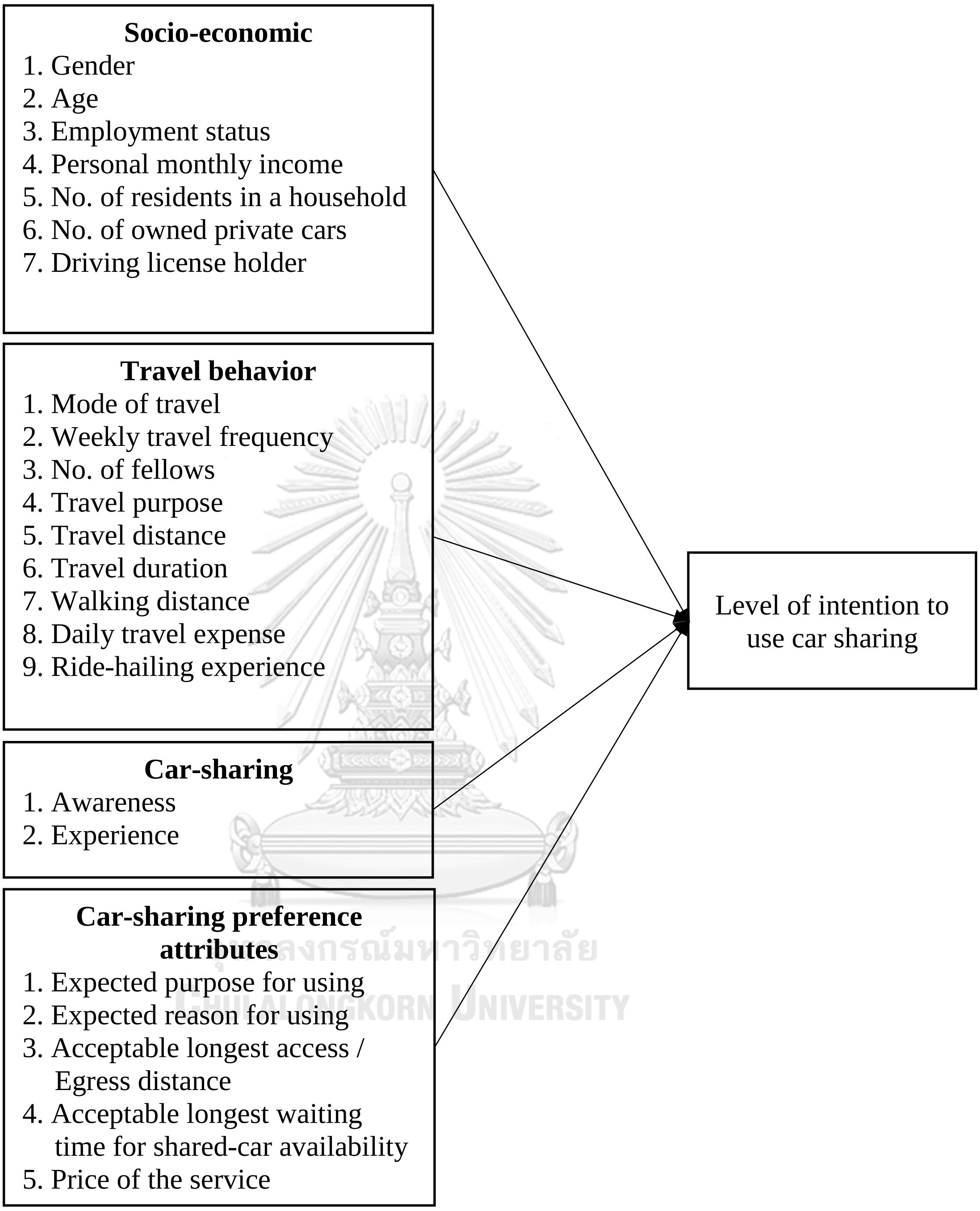


Figure 14 Conceptual framework of Study One

3.1.2 Hypothesis Development and conceptual framework of Study Two

This study employed the TAM framework as it is more powerful for predicting users' intention to use a new technology than TRA and TPB. However, the weakness of the TAM model is it generally includes only two variables for predicting the behavioral intention to use new technology. The researcher believes that it is insufficient, since there are more antecedents that drive the adoption of car sharing. Subjective norm or social influence are included in TRA and TPB, whereas TAM does not specify this factor. However, social influence is an important factor leading to motivation for consumption as behavior intention (Giang et al., 2017).

The knowledge of personal characteristics is a useful way of increasing the predictive power of TAM (Y.-H. Cheng & Huang, 2013). Car sharing is considered as a sustainable form of transport. So, this type of service attracts the people with environmental concerns (Müller, 2019). In addition, car sharing is typically driven by mobile technology. The people who naturally feel encouraged try out and accept innovations across multiple technologies tend to be willing to adopt new technology. Thus, the individual factors of environmental concern and personal innovativeness should play a critical role in the early stages of a car-sharing services.

However, people may be concerned about new technology, especially the technology with both online and offline technology like car sharing. The physical characteristics and technological operation systems of car-sharing service may uncertainty when using. Perceived risk can lower the customers' positive attitude toward the new technology. Thus, perceived risk can affect the decision to use car-sharing services.

To sum up, this study conducted quantitative analysis of technology acceptance of car sharing by employing the technology acceptance model (TAM) with the extended variables of personal innovativeness, environmental concern, social influence and perceived risk.

3.1.2.1 Hypothesis development

1) The Technology Acceptance Model (TAM)

TAM has been applied as a theoretical model in various fields. Thus, the relationship between constructs within the TAM have been confirmed by various studies for many technologies (Müller, 2019). Also, many empirical studies supported the relationship between constructs of TAM on car-sharing services.

In the TAM model, perceived usefulness (PU) and perceived ease of use (PEOU) are the main factors influencing the attitude towards new technology, which directly affects the behavioral intention to use the new technology. In turn, it is an indicator of technology acceptance.

The usefulness of the target technology is a critical determinant of user behavioral decisions (J. Lu, 2014). Perceived usefulness has been found to positively influence on the attitude toward using car sharing services (Giang et al., 2017; H. Kim et al., 2017; Müller, 2019), ride sharing (Müller, 2019) and bike sharing (P. Cheng, OuYang, & Liu, 2019).

Perceived ease of use is another main factor determining technology acceptance. The positive relationship of PEOU on attitude was found on the use of car sharing (Müller, 2019) , ride sharing (Giang et al., 2017), bike sharing (P. Cheng et al., 2019). However, Jayasingh and Eze (2010) found that PEOU is not as critical a determinant factor of user behavioral decisions as the PU, this is because PEOU has a direct impact on the post-adoption stage rather than the pre-adoption stage.

According to the TAM, PEOU affects the behavioral intention through PU. Davis (1989) and E. S.-T. Wang and Chou (2014) explained that the easier technology can be used, the less effort it is to use the application. Car-sharing research has also validated this relationship. Müller (2019) found a positive influence of PEOU on PU in relation to car-sharing services.

When people perceived the technology was easy to use, it was likely also to be seen as useful, which in turn led them to form positive attitudes toward the technology (H. Kim et al., 2017). Therefore, people with a positive attitude towards car sharing were more likely to use that new technology (Claasen, 2020). Several studies found the relationship of attitude on intention to use sharing services: car sharing (H. Kim et al., 2017; Müller, 2019), bike sharing (P. Cheng et al., 2019), shared mode (Claasen, 2020) and park and ride services (Ibrahim et al., 2020). According to the TAM framework, the hypotheses are proposed as follows:

H_1: Perceived usefulness positively affects attitude toward car sharing
H_2: Perceived ease of use positively affects attitude toward car sharing
H_3: Perceived ease of use positively affects perceived usefulness
H_4: Attitude positively affects intention to use car sharing

2) Individual Factors

The number of researchers suggested that personal characteristics are an external variable that impacts technology adoption. Many studies found that the users of car-sharing systems are generally associated with innovativeness and sustainable behavior.

In terms of personal innovativeness, customers with high levels of innovativeness were more willing to adopt ride-sharing services (H. Kim et al., 2017; Y. Wang et al., 2020). Müller (2019) claimed that there are higher adoption of car-sharing service among innovative customers. H. Kim et al. (2017) revealed that user's innovativeness influences the decision of using car-sharing service. Schlüter and Weyer (2019) found the significant effect of technophilia on EV car-sharing acceptance. Müller (2019) found the influence of innovativeness on the car-sharing acceptance. (Y. Wang et al., 2020) noted that personal innovativeness positively influences the intention of customer to use ride-sharing service through the perceived usefulness and perceived ease of use. They concluded that customers make decisions towards the use of car-sharing based mainly on the convenience and usefulness.

Environmental concern refers to the efficiency of individual mobility, presented as an additional element of preference with the beneficial effects on travel related pollution (Mattia et al., 2019). There is solid evidence that car-sharing could lead to pollution reduction and traffic decongestion (Firnkorn & Müller, 2011; Nijland & Meerkerk, 2017; Martin & Shaheen, 2011; Baptista et al., 2014; Jung & Koo, 2018). Many studies highlight that the customers of car-sharing service tend to be more pro-environmental than the average customers. Mattia et al. (2019) found that environmental concerns drive the intention to re-use free-floating car-sharing. Hjorteset and Böcker (2020) tested the relationship between environmental consciousness on the willingness to use car-sharing. They found that environmental consciousness, covering interest, intention, and participation, was a key factor for car-sharing adoption. Müller (2019) found a relationship between the attitude towards environmental on customer acceptance of car sharing. However, their study also compared the difference from three markets: Europe, North America, and China. They found that environmental attitudes were likely to be a less important factor for Chinese respondents than in other regions. Fleury et al. (2017) found that environmental friendliness had a significant effect on behavioral intention to use a corporate car-sharing service. Barnes and Mattsson (2017) found that the customers' perceive of environmental benefits played a significant influence to the intention to use car-sharing. Y. Wang et al. (2020) found that environmental awareness is positively associate with customers' intention to use ride-sharing service. Schlüter and Weyer (2019) found the influence of ecological awareness on perceived usefulness. Therefore, it can be concluded that customers with sustainability behaviors will determine their understanding and perception of environmental benefits, which in turn will influence their overall perception of car sharing's usefulness.

This study will address the underlying of individual personality in terms of personal innovativeness and environmental concern to understand what characterizes car-sharing interest. Thus, the hypotheses based on these agreements are as follows:

H_5: Personal innovativeness positively affects perceived usefulness
H_6: Personal innovativeness positively affects perceived ease of use
H_7: Environmental concern positively affects perceived usefulness
H_8: Environmental concern positively affects perceived ease of use

3) Social Influence

Individuals tend to follow the people who are important to them. The thoughts or opinions of friends, family or colleagues are important determinants of personal choice intentions (Jing et al., 2019). In the emerging market of car sharing, people may hesitate to use the service, adopting a wait-and-see attitude. Thus, social pressure may play an important role in influencing customers' intention to use car-sharing services. People may seek information or suggestions from the internet. Thus, word-of-mouth or internet reviews also influence the customer decisions on the use of car sharing.

Social influence in this research refers to how other people influence an individual's behavioral intentions, which cover normative social influence and informative social influence (E. S.-T. Wang & Chou, 2014).

Normative social influence or Subjective norm was initially proposed by Fishbein and Ajzen (1975) in the TRA. Several studies have shown that social influence has a significant and positive influence on behavioral intention. Jing et al. (2019)found that subjective norm is the most significant factor affecting travelers' intention to use shared cars. Mattia et al. (2019) found that subjective norm affects the future intention to re-use free-floating car-sharing. Claasen (2020) found that social norm has the largest impact on the intention to use shared mode. Liu and Yang (2018) found that subjective norm affects perceived usefulness and perceived ease of use, thereby influencing behavioral intention.

On the other hand, some studies indicated that the social influence is the weakest indicator of behavior intention to use car sharing, possibly because individuals are able to independently decide to use the services without having to consult other people. Ibrahim et al. (2020) found that subjective norm is the least significant contributor to the intention to use Park & Ride facilities. Barnes and Mattsson (2017) found that social influence does not play a role in customers' intention to rent a car sharing. This is because car-sharing customers appear very independent-minded and opportunistic, and thus social influence may not have affect their activities. Fleury et al. (2017) found that social influence does not impact to the intention to use a corporate car sharing. This is because the car-sharing service had only just been introduced in the author's country, so there were not many users of the service. Venkatesh et al. (2003) explained that social influence only had an impact on the behavioral intention after a period of use.

However, car sharing operates in the form of "Online-platform" where people can seek information on social media or electronic word-of-mouth that is the evidence of reality provided by others to prove that a service is valuable (Myers, 2009; Kim & Choi, 2016). Furthermore, online rating or review scores based on customer experiences are a sign of trustworthiness as proved by other people (Chua et al., 2020). Also, through the online platform, users pay attention to products' ease of use when considering the products' usefulness (Liu & Yang, 2018).

This study investigated Thai people, who are more rely on friends, family, colleagues or other people than Western people who are more individualization. Thus, to determine whether social influence affects PU and PEOU that influence the intention to use car sharing, the hypotheses are proposed as follows:

H_9: Social influence positively affects perceived usefulness

H_{10}: Social influence positively affects perceived ease of use

4) Perceived Risk

As stated above, perceived ease of use and perceived usefulness may have positive effects on the intention to use car-sharing services. However, people might hesitate to use the service due to the risk associated with the new technology or service. Risk is considered as a resistance factor for technology adoption (Y. Wang et al., 2020).

The concept of perceived risk was originally introduced by Bauer (1960) cited by Lu, Hsu & Hsu (2005) . He defined risk as the uncertainty and consequences associated with a consumer's action. Studies have identified various types of perceived risk including financial risk, physical risk, functional risk, social risk, and time loss risk. Featherman and Pavlou (2003) indicated that perceived risk is related to financial, product performance, social, psychological, physical, or time risks in the pursuit of a desired outcome of using products or services. Perceived risk can affect customers' positive perceptions, which in turn lower their confidence in the perceived usefulness toward products or services (Barnes & Mattsson, 2017).

In the context of car-sharing service, risks are associated with both electronic risks and physical risks because the service conflate online and offline. The study of Y. Wang et al. (2020) found that perceived risk is negatively associated with the customers' intention to use ride sharing. The reason behind this finding is that ride sharing heavily relies on a mobile technology which requires customers' personal information and privacy. Somehow, the imperfection of the system may lead to the high security risks. Also, customers may also be nervous and worried about the property safety and physical security, such as accident, when using ride sharing.

Lamberton and Rose (2012) found the perceived risk of product scarcity plays a significant role in determining sharing propensity. They highlighted that the commercial sharing domain requires a consideration of perceived product scarcity risk due to rivalry for the shared products such as shared cars.

Mensah et al. (2019) found that customers' security and privacy protection is an important contributing factor in the engagement with any online service provision or technology. Jing et al. (2019) found that perceived risk had a negative impact on behavioral intention to use shared autonomous behavior.

H. Kim et al. (2017) studied the personal concern, which relates to concerns about personal information protection, on the car-sharing usage intention. From the customers' in-depth interview, privacy concerns were identified as a potential determinant of the car-sharing usage. However, quantitative analysis with SEM revealed that there was no significant effect of personal concern on the intention to use car sharing.

This study investigated the perceived risk in relation to (1) privacy risk, (2) operational risk and (3) physical risk. Privacy risk refers to the potential threat to an individual's information. Operational risk represents the probability that systems might not perform as expected. Physical risk is concerned with the potential risk of the threat from the vehicle.

Based on these arguments, this study will explore the effect of risk to the customers' perceived usefulness and intention to use car-sharing service. The hypotheses were developed as follows;

H_{11}: Perceived risk negatively affects attitude toward car sharing

H_{12}: Perceived risk negatively affects customers' intention to use car-sharing

3.1.2.2 Conceptual framework of Study Two

The conceptual framework regarding to the hypotheses of Study Two is shown in Figure 15.

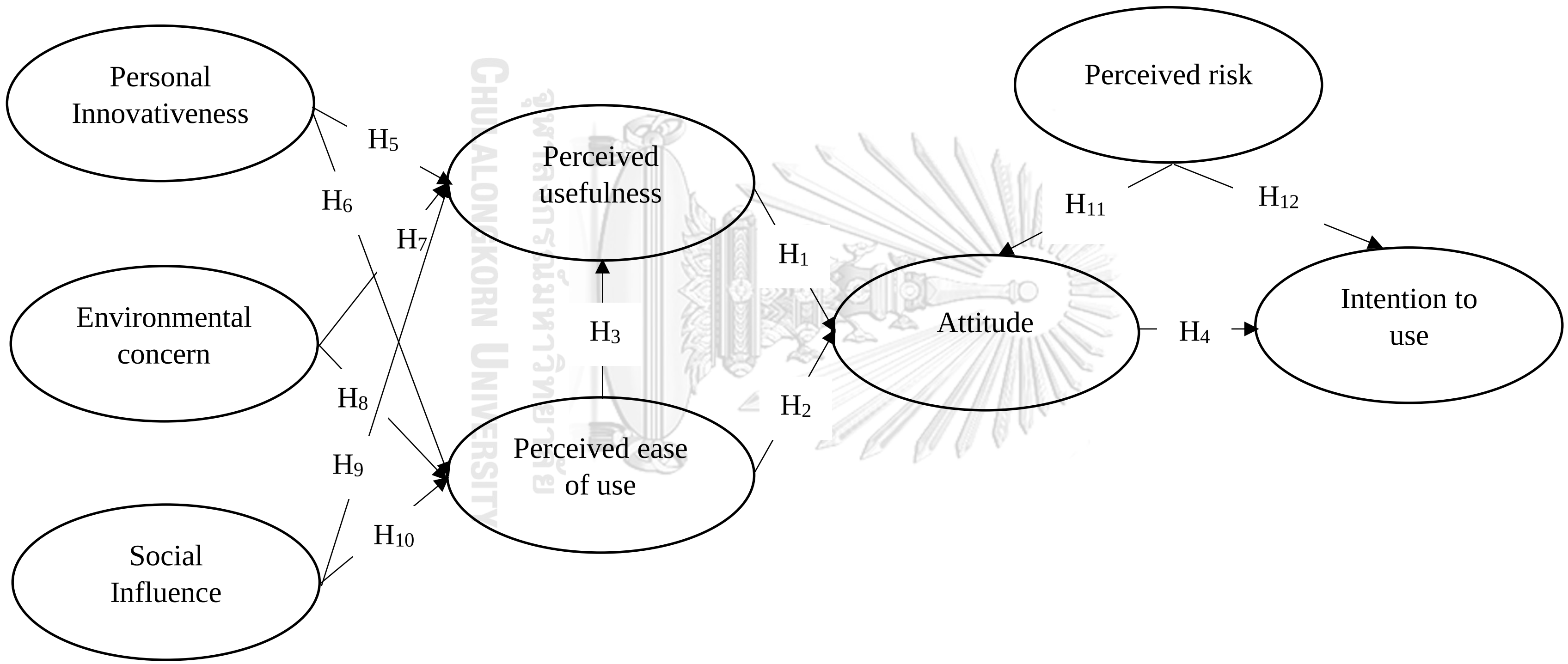


Figure 15 Conceptual framework of Study Two

3.2 Overall research design

Research design is the plan of a research for conducting the study and answering the research questions (Sekaran & Bougie, 2016). The research design is based on the theoretical framework and identified variables (Sekeran, 2003). This current study aimed to examine the factors influencing customers' intention to use car sharing. The survey research approach was used for this study because it gives quantitative or numerical descriptions of trends, attitudes, or opinions expressed by the participants of the study (Creswell & Miller, 2000). The questionnaires were used as research tools for collecting the information on customer types and attitudes on intention to use car-sharing.

This current research consisted of two studies. First study aimed to examine the factors influencing the probability of car-sharing services being used in Bangkok. The research methodology framework of the Study One included three main stages: 1) questionnaire development, 2) data collection process, and 3) data analysis and interpretation process.

Study One applied a stated preference survey, which is a technique of demand estimation through individual preferences in a set of transport options. This study began by selecting study areas and target population, followed by choosing the variables and attributes for questionnaire development. Before using the questionnaire, face-to-face interview and pilot test survey were conducted for testing that the respondents could completely understand the questionnaire, as well as testing the analysis procedure. After that, the main survey was conducted using surveys with online questionnaire. The data were analyzed using multiple regression analysis under the concept of logistic regression. The details of the research methodology framework of Study One is illustrated in Figure 16.

Study Two comprised four main stages: (1) model-framework development by reviewing previous literature, together with interviewing experts, (2) questionnaire development, (3) data collection process, and (4) statistical method for analyzing data, including descriptive statistics and structural equation model (SEM).

Study Two started with a review of the literature associated with the customer acceptance of the new technology to gather all related variables and construct the model. Then, interviews were conducted to determine the variables of the research framework, as well as to support the literature review and hypothesis development in the previous section.

Next, the questionnaire was designed for collecting the primary data in the survey of customers' attitudes toward car-sharing and intention to use car-sharing. The questionnaire consisted of seven questions of personal information, 49 items with a five Likert scale of technology acceptance, and one open-end question. The questions were translated into Thai. Before using the questionnaire, reliability and validity were tested. After the instrument adaptation procedure, the main survey was conducted. The questionnaire was distributed to the target population, people aged over 18 years studying or working in Bangkok.

Finally, the hypothesized model was tested by structure equation modeling (SEM) technique using AMOS software (version 21.0.0). The steps of the research design adopted in Study Two are illustrated in Figure 17.

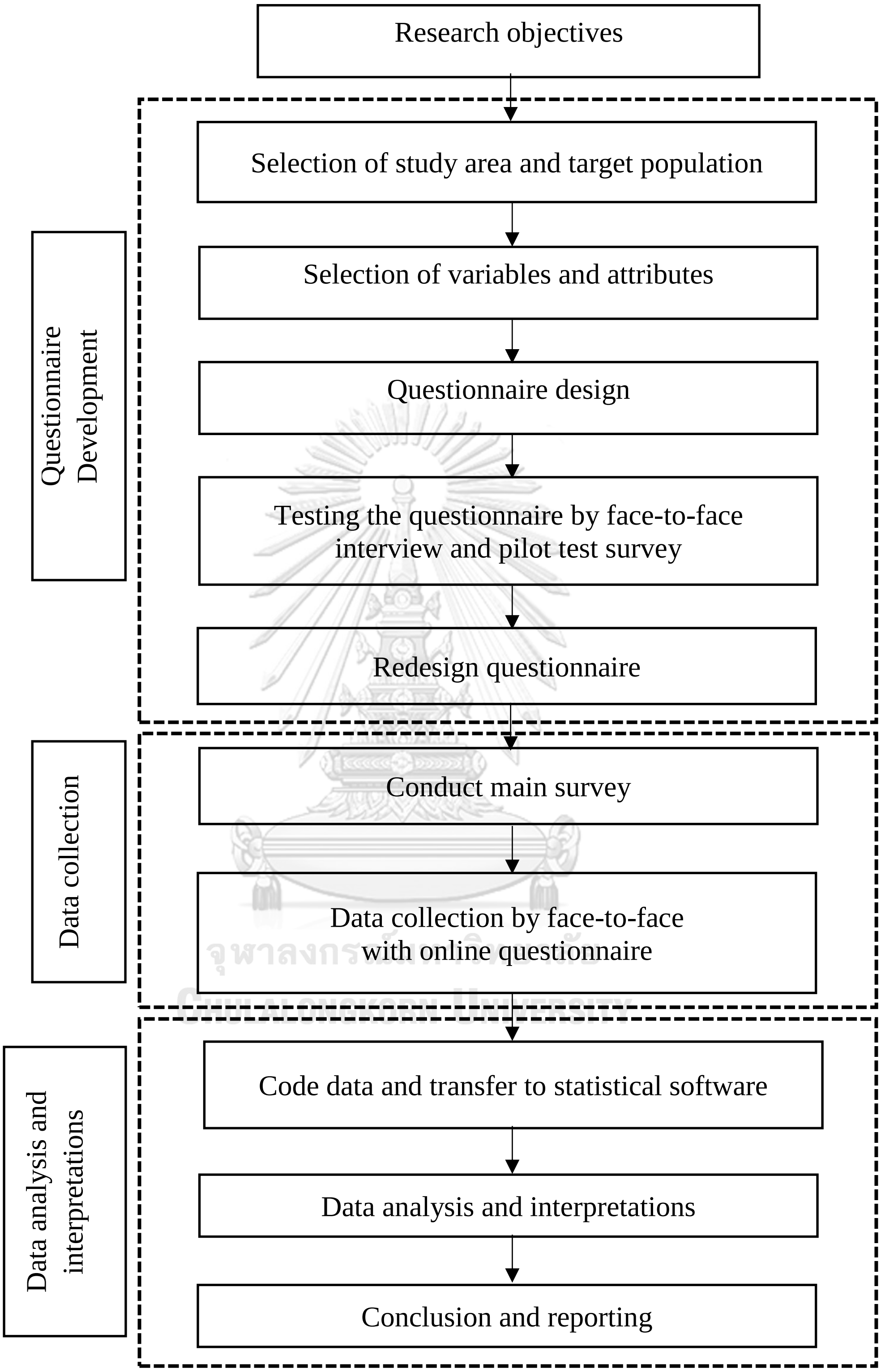


Figure 16 Research methodology framework of Study One

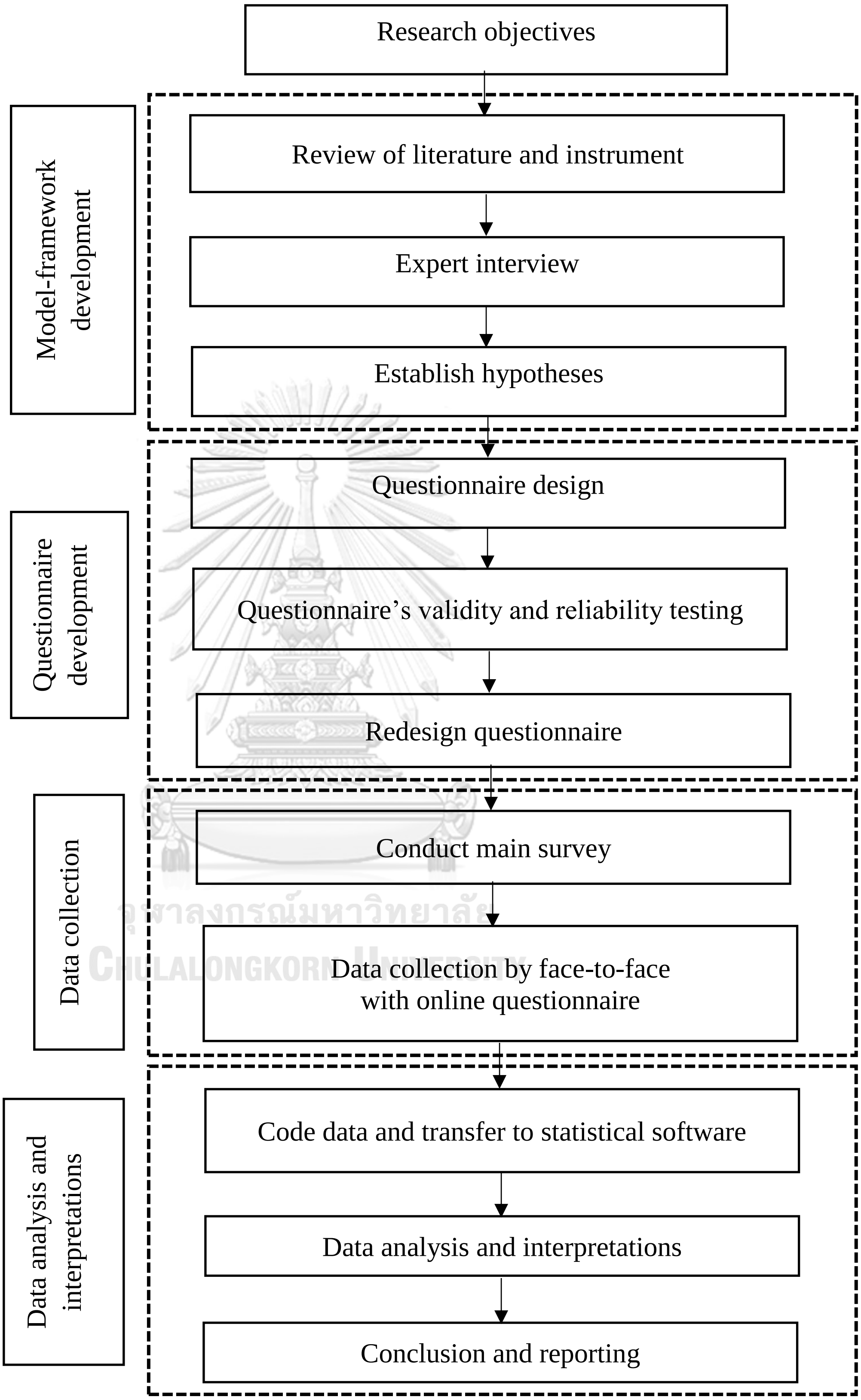


Figure 17 Research methodology framework of Study Two

3.3 Research methodology of Study One

3.3.1 Study Area

Generally, a study area for transportation purposes relates to a geographical region in which transport planning needs to be done. The study area is important for estimating and forecasting the travel demands of target population in terms of accurate information and statistics. Residents in the area usually determine the travel mode, along with their significant attributes (Khan, 2007).

Bangkok was selected as the study area for this research for two main reasons: firstly, Bangkok is the business area where millions of people travel within and across every day; it has the country’s worst traffic conditions, including traffic jam and insufficient parking space; secondly, the Bangkok area has good public transportation networks, one of the key success factors for car-sharing systems.

The total area of Bangkok is around 1,569 km^2. The registered population in Bangkok in 2019 was 5,666,264 people with 3,041,115 households. Thus, the population density was 3,612 people/km^2, that was relatively high density (Administrative Strategy Division, 2019).

The raising of the population in the metropolitan has led to higher transportation demands. According to the Travel Demand Survey project of Transport and Traffic Planning and Policy Office (2018), the majority of people in Bangkok traveled by private car, accounting for 39.90%; the main trip objective was for work, starting from home and ending at home (around 65%). In addition, the total trips in Bangkok were 32.65 million trips per day. Most of the trips were in Bangkok, accounting for 54.20%, followed by trips between Bangkok and perimeter provinces (Samutprakarn and Nonthaburi), accounting for 2.40 and 2.05, respectively. The travel information in Bangkok is shown in Table 3-1.

Table 7 Travel information in Bangkok in 2017

Information	Result
1. Car ownership rate per household	
1.1 Car	0.98 car per household
1.2 Motorcycle	0.77 motorcycle per household
2. Trip purpose	
2.1 Home base work	64.40%
2.2 Home base education	14.20%
2.3 Home base other	13.20%
2.4 Non-home base work	8.10%
3. Average number of trips	1.97 trips per day
4. Types of travel	
4.1 Private car	39.90%
4.2 Private motorcycle	23.80%
4.3 Public transport	29.50%
4.4 School bus / Shuttle bus	2.10%
4.5 Taxi / Motorcycle taxi	4.60%
4.6 Others	0.30%

Table 7 (Continue)

Information	Result
5. Average trip distance	12.64 km.
6. Average trip duration	33 mins
7. Average speed of travel	22.70 km./hr.
8. Average trip cost	32 Baht/trip

Source: Transport and Traffic Planning and Policy Office (2018)

3.3.2 Stated Preference (SP) Methods

"Stated preference" refers to a family of approaches that estimate utility functions by analyzing individual respondents' statements about their preferences in relation to a set of transport alternatives (Kroes & Sheldon, 1988). They are one of the key tools for demand analysis.

There are two broad types of response strategies in travel behavior research: (i) the respondents are asked about the preferences among a set of combinations of attributes that define services or products. The measurement scale used in this strategy is usually either a rank ordering or a rating scale. For example, with ranking questions, the respondents need to rank the alternatives in order from least favorite to most favorite. Meanwhile, the rating type requires respondents to score each possible numeric value between zero and ten (for example). (ii) the respondents are tasked with selecting one of the attribute combinations (Hensher, 1994).

To begin the SP survey, the type of response strategy is needed to determine as it will define the available outputs (Hensher, 1994). This research will apply rating data because

- rating data are the most comprehensive statistic since they include both order and degree of preference
- Over the whole rating scale, the size of the reaction to any attribute combination might vary

3.3.3 Questionnaire design

Stated preference experiment generally comprises five key steps design process (Hensher, 1994) which can be summarized as follows:

Task 1 Identification of the set attributes. In this task, sources of influence users' preference need to be identified. In order to identify the set attributes, the researcher could choose via a preliminary survey (such as pilot survey or focus group), a literature review from previous studies or factors in which the researcher is interested. The list of attributes is shows in Table 8.

Task 2 Selecting the measurement unit for each attribute. For the new alternative technology, some metrics for an attribute are ambiguous, thus researcher needs to clarify a description of the attribute for the accuracy in the latter information. The measurement of each variable shows in Table 8.

Task 3 Specification of the number and magnitudes of attribute levels. The number of levels for each attribute will be decided by the overall complexity of the design.

Task 4 Statistical design. A combination of attribute levels describes as an alternative which is generated with the aid of statistical design theory.

Task 5 Translate the experimental design in task 4 into a set of questions for execution in the data collection phase.

This research used a survey in which the variables and attributes were found from the previous literature and the research questions. The survey comprised four parts as follows:

1) Personal information, related to the data on personal and household characteristics.

2) Travel behavior, related to the current travel mode for a daily trip and travel characteristics of the respondents.

3) Car-sharing preference part was associated with about awareness and previous usage of car-sharing systems, together with preference attributes of car sharing.

4) The last part was price scenarios of car sharing. Respondents had to rate the probability of using car sharing for three price scenarios. They had to rate the choice that they think it provides the highest utility.

Table 8 List of variables in Study One

Variable		**Type**	**Description**
Dependent variable			
	The probability of using car sharing	Scale	The score of the probability of using car sharing from 0-100
Independent variables			
Personal information	Gender	Nominal	- Male - Female
	Age	Ordinal	- Under 20 - 20 – 40 years old - 41 – 60 years old - More than 60 years old
	Employment status	Nominal	- Under education - Employed (part-time) - Employed (full time) - Employed (self-employed) - Unemployed
	Personal monthly income	Ordinal	- Less than 20,000 Baht - 20,000 – 40,000 Baht - 40,001 – 60,000 Baht - More than 60,000 Baht
	Number of residents in a household	Scale	Number of residents in a household
	Number of owned private cars	Scale	Numbers of owned private car
	Driving licensing	Nominal	-Yes / No

Table 8 (continue)

Variable		Type	Description
Travel Behavior	Mode of travel	Nominal	- Private car as a driver - Private car as a passenger - Public transport
	Weekly travel frequency	Scale	Numbers of travel days per week
	Number of fellows	Scale	Specify the numbers of people who usually travel with
	Travel purpose	Nominal	- For working or studying - For visiting friends or relatives - For traveling or relaxing - For shopping - For visiting a doctor - Others
	Travel distance	Scale	Average travel distance in kilometers
	Travel duration	Scale	- Average travel time in minutes
	Walking distance	Scale	- Average walking distance from home/office/university to car park or public transport station in meters
	Daily travel expense	Scale	- Average travel expense in Thai Baht
Ride hailing experience and using characteristics	Ride-hailing experience	Nominal	Yes / No
	Frequency of using ride-hailing	Nominal	- Less than once a month - 1-2 times a month - 3-4 times a month - More than 4 times a month - Never used
	Purpose of using ride-hailing	Nominal	- For working or studying - For visiting friends or relatives - For traveling or relaxing - For shopping - For visiting a doctor - Others - Never used
	Travel expense of using ride-hailing	Scale	- Average a ride-hailing travel expense in Thai Baht

Table 8 (continue)

Variable		Type	Description
Car-sharing experience and preferences	Awareness	Nominal	-Yes / No
	Experience	Nominal	-Yes / No
	Expected activity of using car-sharing	Nominal	- For working or studying - For visiting friends or relatives - For traveling or relaxing - For shopping - For visiting a doctor - Other
	Expected reason of using car-sharing	Nominal	- For replacing current mode - For traveling during the day - For connecting to other modes of transport
	Acceptable longest walking distance	Scale	Specify the maximum walking distance to the car-sharing station
	Acceptable longest waiting time	Scale	Specify the maximum waiting time for shared car availability
Price scenarios	Price of the service	Scale	- Service price 100 Baht / hour and fuel price 6 Baht / kilometer - Service price 120 Baht / hour and fuel price 6 Baht / kilometer - Service price 140 Baht / hour and fuel price 6 Baht / kilometer

3.3.4 Population and Sample

The standard framework of demand estimation requires data that can represent the targeted population's characteristics. The population of this research was the people who aged over 18, living, studying or working in Bangkok.

The sample may be described as a group of individuals who have been specifically chosen to represent a wider population with certain characteristics of interest. However, there are no simple and objective solutions to the sample size computation in every circumstance (de Dios Ortúzar & Willumsen, 2011).

From Hsieh (1989)'s table of the sample size of logistic regression, if the number of events is 100, the sample size should be 200. de Dios Ortúzar and Willumsen (2011) claimed that 75-100 samples are sufficient for stated preference method because one sample can answer many scenarios. Thus, this study will use at least 200 samples.

3.3.4.1 Sampling technique

There are two primary methods of sampling: probability and non-probability sampling. A probability sampling technique is one in which the sample is drawn randomly from the population and each unit in the population has a known probability of being chosen (Bryman, 2016). Meanwhile, for a non-probability sampling approach, a sample is selected based on the researcher's judgement, experience, or convenience (Cohen, Manion, & Morrison, 2017). The various types of sampling technique are shown in Figure 18.

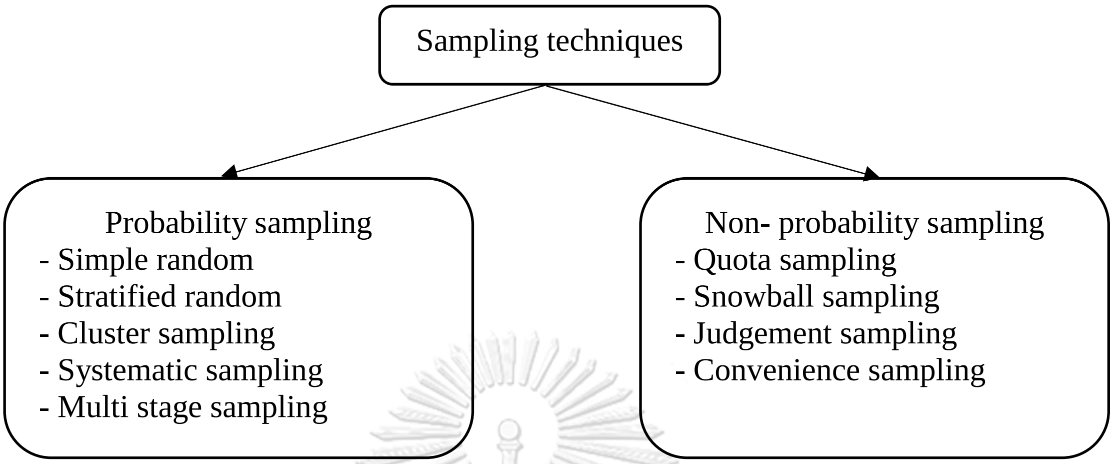


Figure 18 Sampling techniques
Sources: Adapted from Custódio (2018)

3.3.4.2 Sampling procedure

The selection of sampling technique is important to ensure the accuracy results of the study. In this research, multi-stage sampling was considered as an appropriate technique because of time and cost constraints. In addition, multi-stage sampling was proper to the large-scale population.

Multi-stage sampling is a method for moving from a large to a small sample size via a step-by-step procedure. The primary objective of multi-stage sampling is to concentrate samples in a few geographical locations (Taherdoost, 2016). The steps of multi stage sampling for this research were described as follows:

1) The population was divided into clusters according to the zoning classification of Administrative district offices of Bangkok (2012). In total, there were six regions of administrative district offices.

(1) Central Bangkok comprising of nine districts: Phra Nakorn district, Dusit district, Pom Prap Sattru Phai district, Samphanthawong district, Din Daeng district, Huai Khwang district, Phaya Thai district, Ratchathewi district and Wang Thonglang district.

(2) South Bangkok consisting ten districts: Pathum Wan district, Bang Rak district, Sathon district, Bang Kho Laem district, Yan Nawa district, Khlong Toei district, Vadhana district, Phra Khanong district, Suan Luang district and Bang Na district.

(3) North Bangkok including seven districts: Chatuchak district, Bang Sue district, Lat Phrao district, Lak Si district, Don Mueang district, Sai Mai district and Bang Khen district.

(4) East Bangkok composed of nine districts: Bang Kapi district, Saphan Sung district, Bueng Kum district, Khan Na Yao district, Lat Krabang district, Min Buri district, Nong Chok district, Khlong Sam Wa district and Prawet district.

(5) North Thonburi comprising eight districts: Thon Buri district, Khlong San district, Chom Thong district, Bangkok Yai district, Bangkok Noi district Bang Phlat district, Taling Chan district and Thawi Watthana district.

(6) South Thonburi including seven districts: Phasi Charoen district, Bang Khae district, Nong Khaem district, Bang Khun Thian district, Bang Bon district, Rat Burana district and Thung Khru district.

2) From six regional clusters, a simple random sampling technique was applied within each regional cluster. The number of samples of each cluster was calculated according to the number of populations in the cluster. The sample size of each regional cluster is shown in Table 9.

Table 9 The sample size of each regional cluster

	Population	Sample size
Central Bangkok	522,832	23
South Bangkok	638,060	28
North Bangkok	873,107	38
East Bangkok	1,058,442	47
North Thonburi	691,087	30
South Thonburi	771,913	34
Total	4,555,441	200

Source: Administrative Strategy Division (2019)

3.3.5 Data Collection Method

Before running the main survey, a pilot survey of 30 respondents was performed to test that the respondents could completely understand the questionnaire. The main questionnaire survey was conducted between June and July 2020, during the Covid-19 pandemic when people were highly concerned about hygienic conditions. Therefore, the survey was conducted through an online survey. The respondents were given a QR code for the online questionnaire, so that they were able to complete the questionnaire through Google form. The questionnaire's QR code was distributed in public places such as bus stops, shopping malls, offices and universities.

3.3.6 Data analysis

3.3.6.1 Stated preference data analysis

This section presents Stated Preference (SP) analysis and SP interpretation. SP data analysis guidelines can be found in the studies of Liao (1994), Borooah (2002), Dickinson (2010) and Baetschmann, Staub, and Winkelmann (2015).

Most of the SP studies were based on the behavioral principle (Random Utility Theory: RUM). The assumption of this theory is that travelers will select the option that provides the greatest satisfaction or 'utility'. Utility, U_{ni}, is hypothesized to be a function of both observable (or predictable) utility and unobservable (or random) utility.

Specifically:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

Where,

U_{ni} is the net utility function for alternative *i* by decision-maker *n*
V_{ni} is the deterministic utility derived for alternative *i* by decision-maker *n*
ε_{ni} is the error component of utility for alternative *i* by decision-maker *n*.

This research employed logit-type modelling, ε_{ni} is assumed to be independently and identically Gumbell distribution (IID assumption) and the ratio of the choice probability for the traveler is unaffected by the systematic utilities of all other alternatives (independence from irrelevant alternatives, IIA property). The binary logit model is applied to model the traveler's decision related to probability of choice to utility as follows:

$$P_{ni} = \frac{e\ \mu Vni}{\sum_{ni' \in J} e\ \mu Vni} \tag{2}$$

Where P_{ni} represents the probability of the traveler *n* to choose the option *i*. However, the SP data in this study is rating data, thus the model suit for this kind of data is the ordered logit model which also known as the cumulative logistic model.

3.3.6.2 Multiple linear regression under a concept of logistic regression analysis

Multiple linear regression under a concept of logistic regression analysis was implemented to investigate the factors influencing the probability of car-sharing services being used in Bangkok.

From the logistic regression theory, the logistic model predicts the logit of *Y* from *X*, and the logit is the natural logarithm (ln) of odds of *Y*, and odds are ratios of probabilities (P) of *Y* happening to probabilities (1-P) of *Y* not happening (Peng, Lee, & Ingersoll, 2002).

The simple logistic model has form

$$\text{Logit } (Y) = \textit{natural} \log (\textit{odds}) = \text{In } (\frac{P}{1-P}) = \alpha + \beta X \tag{3}$$

To predict the probability of the occurrence of the outcome of interest, the antilog is taken of equation (3) on both sides. One derives an equation is as follows:

$$P = \text{Probability } (Y = \text{outcome of interest}) = \frac{e^{\alpha+\beta x}}{1 + e^{\alpha+\beta x}} \tag{4}$$

Where,

P is the probability of the outcome of interest or event
α is Y intercept
β is regression coefficient
e = 2.71828 is base of the system of natural logarithms

The extended logistic model with multiple predictors has a form

$$\text{Logit}\ (Y) = \log\ (\text{odds}) = \text{In}\ \left(\frac{P}{1-P}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \quad (5)$$

In this study, the dependent variable (Y, the probability of car-sharing ranging from 0-100) was modified to exclusive number by dividing by 100, and multiplying by 99, then, adding 0.5. After that, Y was transformed to log odds. Thus, this research applied the concept of logistic model, and constructed the multiple linear regression as

$$\text{In}\ \left(\frac{y}{100-y}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \quad (6)$$

3.4 Research methodology of Study Two

3.4.1 Survey Research Methodology

The survey research method is one of the most frequently utilized data gathering techniques. The survey research approach is a technique for amassing data about people' attitudes, beliefs, knowledge, and behavior (Cohen et al., 2017; Creswell & Miller, 2000; Fink, 2015). This kind of research describes these aspects quantitatively (Creswell & Miller, 2000). In this study, the survey method was chosen for the following reasons:

1) This research attempted to measure the customers' behavior and attitude toward car-sharing acceptance.

2) Since the population of this research was over four million people, the survey method approach is useful for collecting the data from a large amount of population who are distributed across a wide geographical area (Cohen et al., 2017).

3) This research has limited time and financial constraints. The survey method has potential to obtain data within a short period with no extra cost, such as travel tickets, telephone bills, etc.

4) The survey research method is popular in measuring the technology acceptance of the customer.

3.4.2 Questionnaire Design

Prior to the stage of questionnaire design, preliminary information was gathered and the study's conceptual framework was developed using information from a literature review and semi-structured interviews.

Sekeran (2003) suggested that the interview method is useful for data collection. With this method, the interviewer can adapt the questions, clarify doubts, and ensure that the respondent can completely understand the question by repeating or rephrasing the question. Moreover, the researcher can obtain more and various information than questionnaire method. Therefore, this study employed semi-structured interviews to gather the preliminary information. The results from the interviews were used to determine the variables of the research framework, as well as to support the literature review and hypothesis development in the previous section.

Face-to-face interview with open-ended questions were conducted between November and December 2020. There were 11 interviewees including four respondents who traveled by public transport, four respondents who traveled by driving their own cars, two experts in innovation and product sharing providers, and one academician in marketing area. The questions aimed to investigate the factors influencing the decision to adopt car sharing. The information from the interviews provided the details of opinions associated with the specific variables with additional insights of possible determinants. After this stage, the researcher was able to focus on the factors which further determined to the development of model framework and questionnaire survey.

The information from the review of literature and interviews was important to the model framework development and variable selection, which in turn shaped the questionnaire development. The questionnaire contained two sections, the details of each as follows;

Section 1 related to the respondents' personal information, comprising seven check-list items: gender, age, occupation, personal monthly income, number of owned private cars, daily mode of travel and car-sharing experience.

Section 2 car-sharing acceptance in Bangkok, which was important for testing the model in this research. The questions were derived from the model framework, which comprising of eight constructs. The constructs could be categorized into two groups: one based on the basic TAM variables, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude toward car sharing (ATT) and Intention to use (INT); the latter dealt with the extended variables that were expected to influence customers' intention to use car sharing, including Personal Innovativeness (PI), Environmental Concern (EC), Social Influence (SI) and Perceived Risk (PR). This section included 49 questions using a five Likert scale ranging from strongly agree (5) to strongly disagree (1). The list of variables used in this section is shown in Table 10.

Table 10 List of variables used in Study Two

Construct	**Item**	**Source**
Personal innovativeness (PI)		Yang and Choi (2001); J. Lu (2014); H. Kim et al. (2017); Müller (2019); Schlüter and Weyer (2019); Y. Wang et al. (2020)
	I usually try a new mobile-based service such as Grab or Lineman.	
	I would not hesitate to try out a new mobile application.	
	I am able to understand mobile application quickly.	

Table 10 (continue)

Construct	Item	Source
Environmental concern (EC)		Barnes and Mattsson (2017); Dall Pizzol et al. (2017); Müller (2019); Schlüter and Weyer (2019); Y.Wang et al. (2020)
	I am concerned about the world's future environment.	
	I think that human consumption today will cause environmental problems in the future.	
	I consider the potential environmental impact of my actions when making my decisions.	
	I am willing to be inconvenienced in order to take actions that are more environmentally friendly.	
Social Influence (SI)		Jayasingh and Eze (2010); J. Lu (2014); Fleury et al. (2017); Jing et al. (2019); Mattia et al. (2019); Ibrahim et al. (2020)
	If my friends or colleagues use car sharing, I will also use car sharing.	
	If a member of my family uses car sharing, I will also use car sharing.	
	If famous people use car sharing, I will also use car sharing.	
	Car sharing advertising will persuade me to use it.	
	The reviews of real user will courage the use of car sharing.	
Perceived Risk (PR)		
	Personal Information risk (PIR)	X.-S. Lu et al. (2015); H. Kim et al. (2017); P. Cheng et al. (2019); N. Kim, Park, and Lee (2019); Y. Wang et al. (2020)
	I am concerned that my personal information will be shared or sold to others when enter the car-sharing platform.	
	I am concerned about unauthorized users gaining access to my account.	
	Payment method would be unsafe.	
	Functional risk (PFR)	X.-S. Lu et al. (2015); Jing et al. (2019); N. Kim et al. (2019)
	I am afraid of transaction error	
	The system would be unstable, causing issues with its use.	

Table 10 (continue)

Construct	Item	Source
Perceived Risk (PR)		
	Physical risk (PPR)	Lamberton and Rose (2012); X.-S. Lu et al. (2015); Dall Pizzol et al. (2017); N. Kim et al. (2019); Y. Wang et al. (2020)
	I am concerned that a shared-car I want will not be available when I want it.	
	I am concerned about driving an unfamiliar-shared-car.	
	I am worried about using shared cars (such as maintenance, cleanliness, etc.).	
	I am worried about Covid-19 when using shared car.	
	I am concerned about the safety assurance of car-sharing service in case of an accident.	
	I am concerned about criminal activity that may occur while using car-sharing service.	
Perceived Usefulness (PU)		
	Cost saving (PUS)	Barnes and Mattsson (2017); Dall Pizzol et al. (2017); H. Kim et al. (2017); Mattia et al. (2019); Y. Wang et al. (2020)
	Using car sharing can save the cost of car ownership	
	Using car sharing can save the travel expense	
	Car sharing is safer than other modes of transportation service.	
	Convenience (PUC)	Lamberton and Rose (2012); Dall Pizzol et al. (2017); H. Kim et al. (2017); P. Cheng et al. (2019); Y. Wang et al. (2020)
	Using car sharing, I could drive a new car.	
	Using car sharing, I could choose a car suiting to my traveling purpose.	
	Using car sharing, I could access and return a shared car at many drop points.	
	Using car sharing, I could use a shred car when I want to.	
	Car sharing is convenient and flexible	
	Car sharing would enable me to get to my destination more quickly.	
	Economic and Social (PUE)	Barnes and Mattsson (2017); P. Cheng et al. (2019); Müller (2019); Y. Wang et al. (2020)
	Car sharing can mitigate traffic problems	
	Car sharing can reduce greenhouse gas emission and energy consumption.	
	Car sharing can reduce a number of car parking spaces.	

Table 10 (continue)

Construct	Item	Source
Perceived Ease of Use (PEOU)		
	I think it is easy to understand how to use car-sharing service.	P. Cheng et al. (2019); N. Kim et al. (2019); Müller (2019); Schlüter and Weyer (2019); Y. Wang et al. (2020)
	I think it is easy for me to use car sharing.	
	I think it is convenient to use car sharing.	
	The use of car sharing does not require much effort.	
	I would have no problem if I used car- sharing service.	
Attitude toward car sharing (ATT)		H. Kim et al. (2017); P. Cheng et al. (2019); Kim, Park & Lee (2019); Müller (2019); Ibrahim et al. (2020)
	I like the concept of car sharing	
	Car sharing is beneficial to society	
	Car sharing is beneficial to the environment	
	Car sharing is beneficial to daily life	
Intention to use car sharing (INT)		P. Cheng et al. (2019); Jing et al. (2019); N. Kim et al. (2019); Mattia et al. (2019); Y. Wang et al. (2020)
	I am interested in car sharing.	
	I intend to use car sharing for traveling in the future.	
	I plan to use car sharing instead of buying a new car.	
	I will inform others of the goodness of this service.	
	I support car sharing as a new phenomenon in society.	

Once finalized, the questionnaire was translated into Thai because the survey was conducted in Thailand and Thai people normally use Thai language. Then, the questionnaire’s validity and reliability were tested.

The instrument's validity refers to the degree to which the data obtained accurately represent the phenomenon being studied (Kripanont, 2007). According to Joseph F Hair, Black, Babin, Anderson, and Tatham (2006), content validity or face validity assesses the relationship between individual questions and concepts by expert judgment and pre-testing with various sub-populations or other techniques. This current research applied expert judge strategy which the experts were asked to judge whether the questionnaire measures the desired content (Bell, Bryman, & Harley, 2018; Sekaran & Bougie, 2016). In this stage, three experts from relevant academic fields reviewed the questionnaire. The details of these experts are given in Table 11.

Table 11 The examiners of content validity

Expert	Position	Affiliation
1. Phairoj Butchiwan, Ph.D.	Head of Management program	General Management Program, Faculty of Management Science, Phranakorn Rajabhat University

Table 11 (continue)

Expert	Position	Affiliation
2. Sun Olapiriyakul, Ph.D.	Assistant Professor	School of Manufacturing Systems and Mechanical Engineering (MSME), Sirindhorn International Institute of Technology (SIIT), Thammasat University
3. Punsawadee Pongsiri, Ph.D.	Assistant Professor	Industrial Business and Logistics Management Program, Faculty of Business Administration, King Mongkut's University of Technology.

Then, the questionnaire was revised, with several words and statements changed for more appropriate words and terms, and more items, that could influence the use of car sharing in current situation such as the concern with Covid-19, were added.

Next, a pilot test survey was performed to detect any weaknesses of the instrument, together with an examination of its the reliability. Sekaran and Bougie (2016) suggested that the researchers should do the pilot test of theirs studies with a small number of participants. Sekaran and Bougie (2016) explained that a pilot study is used to eliminate wording problems and ensure the clarity of the questionnaire items. Moreover, Ticehurst and Veal (2000) claimed that pilot survey is used in order to test analysis procedures. The scale of the pilot may range from 25-100 subjects (Cooper & Schindler, 1998). Thus, the pilot survey of this study was carried out by online-based questionnaire through Google form. The data were collected through the QR code of the questionnaire that was given to the respondents in Bangkok in January 2021. In total, 50 respondents completed the questionnaire.

Data collected from the pilot survey were coded into SPSS software (version 21) to measure the constructs' reliability. Reliability can be defined as the constructs' internal consistency and ability to gathering the same results under the same situations (Field, 2013). The reliability of the questionnaire can be calculated using Cronbach's coefficient alpha (α), which is most often used in traditional social science research (Cronbach, 1951; Sekaran & Bougie, 2016). Sekaran and Bougie (2016) claimed that the number of Cronbach's coefficient alpha over 0.8 is considered as good, in the 0.7 range is considered as acceptable and less than 0.6 is poor. Moreover, Joe F Hair, Ringle, Sarstedt, and Practice (2011) and J. Hair, Hollingsworth, Randolph, and Chong (2017) claimed that the reliability value between 0.6 and 0.7 are acceptable for exploratory research. The results of the internal reliability test of the current study are shown in Table 12.

Table 12 The reliability of the pilot study

Constructs	**Number of indicators**	**Cronbach's alpha**	**Reliability results**
Personal innovativeness (PI)	3	0.729	Acceptable
Environmental concern (EC)	4	0.765	Acceptable
Social influence (SI)	5	0.943	Good

Table 12 (continue)

Constructs	**Number of indicators**	**Cronbach's alpha**	**Reliability results**
Perceived usefulness (PU)	3	0.875	Good
Perceived ease of use (PEOU)	5	0.938	Good
Attitude (ATT)	4	0.941	Good
Intention to use (INT)	5	0.913	Good
Perceived risk (PR)	3	0.847	Good
Total	27	0.966	Good

3.4.3 Population and Sample

3.4.3.1 Population

'Population' refers to the entire gathering of people, units, or objects to which researcher desires to generalize the findings (Sue & Ritter, 2012). The target population in this study was the people over 18 years old living, studying, or working in Bangkok. According to Bangkok Administrative Strategy Division (2019), the registered population over 18 years old was accounting for 4,555,441 in 2019.

3.4.3.2 Sample size

There are numerous techniques for determining the sample size. Three methods considered were considered for this research:

1) According to Yamane's formula (Yamane, 1967), the sample size is calculated from

$$n = \frac{N}{1 + N(e)^2}$$

Where N = Population size, n = Sample size, e = Level of precision

Thus, for this research with N = 4,555,441 at 95% confidence level

$$n = \frac{4{,}555{,}441}{1 + (4{,}555{,}441 \times (0.05)^2)}$$

$$n = 399.96$$

$$\approx 400$$

2) Sue and Ritter (2012) suggested that in multivariate investigations, the sample size should be at least ten times the number of indicators used. The number of indicators in this study was 27 (See Table 12), thus the proper sample size was at least 270.

3) From the use of GPower 3.1 software for a large effect size and power of test was 0.80 (Joseph F Hair Jr, Hult, Ringle, & Sarstedt, 2016), the sample size recommended was 346.

In short, these three calculation methods suggest the appropriate sample size for this research was 270-400 samples. Therefore, this study used at least 400 samples.

3.4.3.3 Sampling technique

According to section 3.2.4.1 (Figure 18), this study also used multi-stage sampling technique for the same reasons of study one: large-scale population, as well as time and cost limitation.

3.4.3.4 Sampling procedure

The sampling procedure in this study followed the multi-stage sampling in Study One (section 3.2.4.2). However, the sample size in this study is larger than Study One, so the sample size of each cluster in this study is shown in Table 13.

Table 13 The sample size of each cluster in study two

	Population	Sample size
Central Bangkok	522,832	46
South Bangkok	638,060	56
North Bangkok	873,107	77
East Bangkok	1,058,442	93
North Thonburi	691,087	60
South Thonburi	771,913	68
Total	4,555,441	400

Source: Administrative Strategy Division (2019)

3.4.4 Data Collection Method

As mentioned earlier, this research used a survey questionnaire based on the model framework. The survey research was conducted in six regions of administrative district offices as shown in Table 3-6. Due to the Covid-19 pandemic, people were highly concerned about hygienic conditions. Therefore, the survey was conducted through an online survey. The questionnaire was created on Google from, then a link to the questionnaire was generated as a QR code. The respondents were given this QR code to access the online questionnaire. The questionnaire's QR code was distributed in public places such as bus stops, shopping malls, offices and universities between January and February 2021.

3.4.5 Analysis Technique

After collecting the data, coding was performed in SPSS version 21. Then, data analysis was performed in two stages: descriptive and interference statistics. For descriptive statistics, the analysis included frequency, percentage and standard deviation by using SPSS. Then, the proposed model was tested using the Structural Equation Modelling (SEM) technique.

Structural Equation Modelling (SEM)

The main purpose of this study was to develop a model of Technology Acceptance that best described the factors influencing the intention to use car sharing in Bangkok. Structural Equation Modelling (SEM) was determined to be the most appropriate method for achieving the research objective.

SEM is a multivariate approach that combines elements of multiple regression (which examines dependency connections) and factor analysis (which represents unmeasured concepts-factors with multiple variables) in order to estimate a series of interrelated dependence relationships simultaneously (Joseph F Hair et al., 2006).

SEM is a methodology that extends first-generation multivariate analysis methods such as factor analysis, regression analysis, and discriminant analysis by allowing for the simultaneous assessing of relationships between independent and dependent variables (Joe F Hair Jr, Sarstedt, Hopkins, & Kuppelwieser, 2014). Joseph F Hair et al. (2006) suggested structure equation modeling (SEM) for analyzing dependent relationships with multiple relationships of dependent and independent variables. Moreover, SEM is widely used for examining the relationships of the variables in TAM model (Barnes & Mattsson, 2017; Fleury et al., 2017; H.Kim et al., 2017; Mensah et al., 2019) .

Chapter 4

Results

This chapter provides results of the data collection from participants in Bangkok. In both Study One and Study Two, the data were collected through online-questionnaire survey, using Google form. After finishing the data collection process, the data were exported from Google sheet to Excel (xlsx) format. Then, data were encoded to Statistical Package for the Social Science (SPSS), version 21. However, the two studies had different analyses. The results of the applied methods and analyses will be presented as follow;

4.1 Results of study one
- 4.1.1 Data
- 4.1.2 Descriptive Analysis
- 4.1.3 Mean Difference Test
- 4.1.4 Multiple linear regression analysis under a concept of logistic regression

4.2 Results of study two
- 4.2.1 Data
- 4.2.2 Descriptive Analysis
- 4.2.3 Preliminary data analysis
- 4.2.4 Confirmatory factor analysis (CFA)
- 4.2.5 Structural equation model (SEM)

4.1 Results of study one

4.1.1 Data

The questionnaire survey was conducted through an online-questionnaire survey and distributed in public places such as bus stops, shopping malls, offices, and universities. The target group was selected by age older than 18 years old living, studying, or working in Bangkok. In total, 204 respondents completed the questionnaire. However, there are three scenarios for each respondent. Thus, there are 612 observations in total.

4.1.2 Descriptive Analysis

4.1.2.1 Socio-economic status of respondents

Seven variables of socio-economic status were analyzed and presented in Table 14. The majority of the respondents were female (63.2%), which was higher than male (36.8%). Most of the respondents (69.5%) were aged between 20 and 40, which was expected to be the age group of target users of car-sharing services. The main employment group was other full-time workers (61.3%), and their personal monthly income was less than 20,000 Baht (37.7%). Twenty-four percent of the participants were living with three people in their household (total of four people per household). Most of the respondents (42.2%) possessed one car, and held a driving license (72.5%)

Table 14 The socio-economic status of the respondents

Socio-economic		**Frequency**	**Percentage**
Gender	Male	225	36.8
	Female	387	63.2
Age	18 - 20	15	2.5
	20 – 40	426	69.5
	41 - 60	162	26.5
	More than 60	9	1.5
Employment status	Students	84	13.7
	Business owner / Freelance	75	12.3
	Full time	375	61.3
	Part time	15	2.5
	Retired / Unemployed	63	10.2
Personal monthly income (Thai Baht)	Less than 20,000	231	37.7
	20,000 – 40,000	207	33.8
	40,001 – 60,000	99	16.2
	More than 60,000	75	12.3
Number of residents in a household	Living alone	84	13.7
	2 people	138	22.5
	3 people	108	17.5
	4 people	147	24.0
	5 people	75	12.2
	More than 5 people	60	9.8
Number of owned private cars	Zero	219	35.8
	1 car	258	42.2
	2 cars	81	13.2
	3 cars	36	5.9
	More than 3 cars	18	2.9
Driving license holder	Yes	444	72.5
	No	168	27.5
Observation (N=612)			

4.1.2.2 Travel behaviors

As shown in Table 15, most of the respondents used a personal car (as a driver), accounting for 53.4%, followed by public transport (34.8%), and personal car as a passenger (11.8%), respectively. The largest group of participants (33.3%) traveled five days a week and the second largest group (26%) traveled seven days a week (26.0%). The majority of them (64.7%) travelled alone. The travel purpose was mainly concentrated in work or study (88.2%).

Table 15 Travel behavior of the respondents

Travel behavior		**Frequency**	**Percentage**
Mode of travel	Personal car (as a driver)	327	53.4
	Personal car (as a passenger)	72	11.8
	Public transport	213	34.8
Weekly travel frequency	1 day	9	1.5
	2 days	39	6.4
	3 days	51	8.3
	4 days	33	5.4
	5 days	204	33.3
	6 days	117	19.1
	7 days	159	26.0
Number of fellows	None	396	64.7
	1 people	156	25.5
	2 people	45	7.5
	3 people	6	1.0
	4 people	9	1.5
Travel purpose	Work or study	540	88.2
	Visit friends or family	9	1.5
	Travel or relax	15	2.5
	Shopping	42	7.0
	Visit doctor	6	1.0
Observation (N=612)			

The average travel distance was 27.11 kilometers, average travel duration was 74.15 minutes, average walking distance from home to car park or bus stop was 183.50 meters, average walking distance from office / university to car park or bus stop was 212.09 meters, and the daily travel expenditure was 139.92 Baht. The majority of the respondents had an experience of using ride-hailing services or mobile-app taxis (79.9%). Mean and standard deviation of scale variables of travel characteristics of the respondents were demonstrated in Table 16 and Figure 19 to 23.

Table 16 Mean and standard deviation of scale variables of travel characteristics

Travel behavior	$\bar{x}$	**S.D.**
Travel distance (km.)	27.11	25.69
Travel duration (mins)	74.15	69.26
Walking distance from home to car park or bus stop (m.)	183.50	350.42
Walking distance from office / university to car park / bus stop (m.)	212.09	377.13
Daily travel cost (Baht)	139.92	133.91

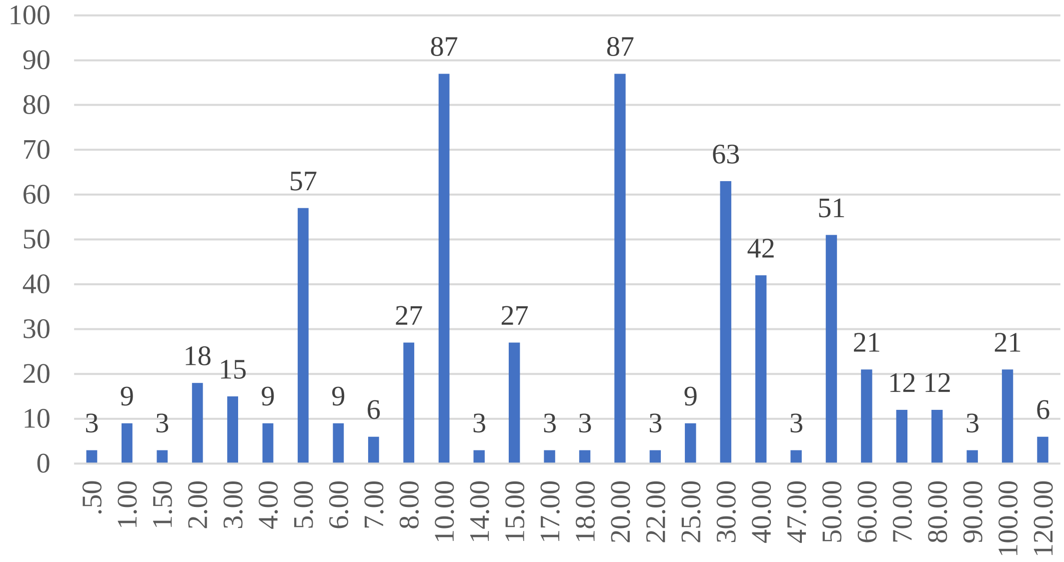


Figure 19 Frequency of Travel distance (km.)

From Table 16 and Figure 19, the travel distance ranged from 0.50 – 120 kilometers. The highest frequency was equally in 10 km. and 20 km. The average travel distance was 27.11 km.

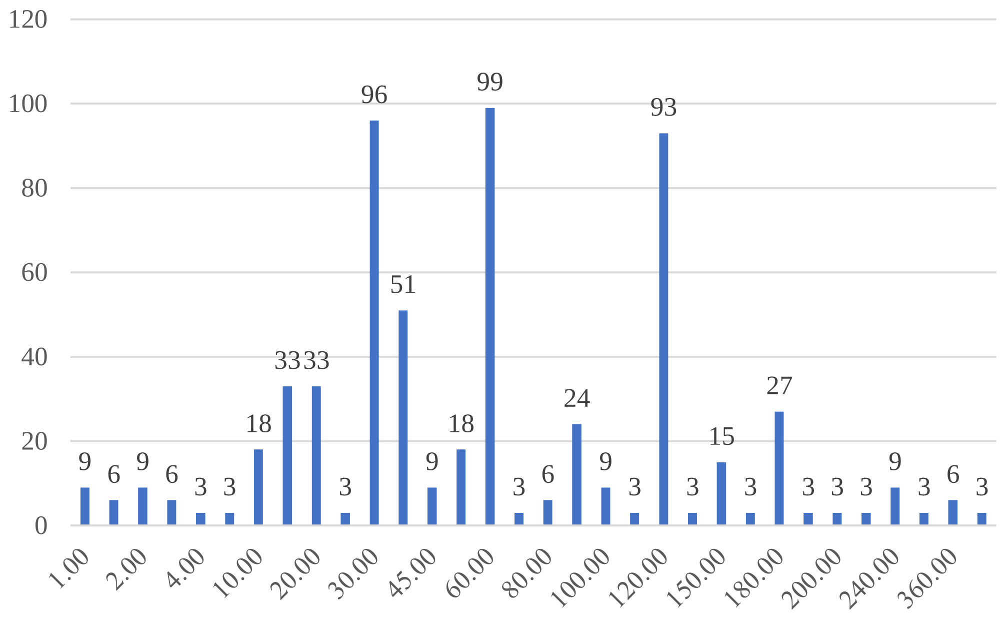


Figure 20 Frequency of Travel duration (mins.)

From Table 16 and Figure 20, the travel duration ranged from 1.00 – 480 minutes. The highest frequency was 60 minutes. The average travel time was 74.15 minutes.

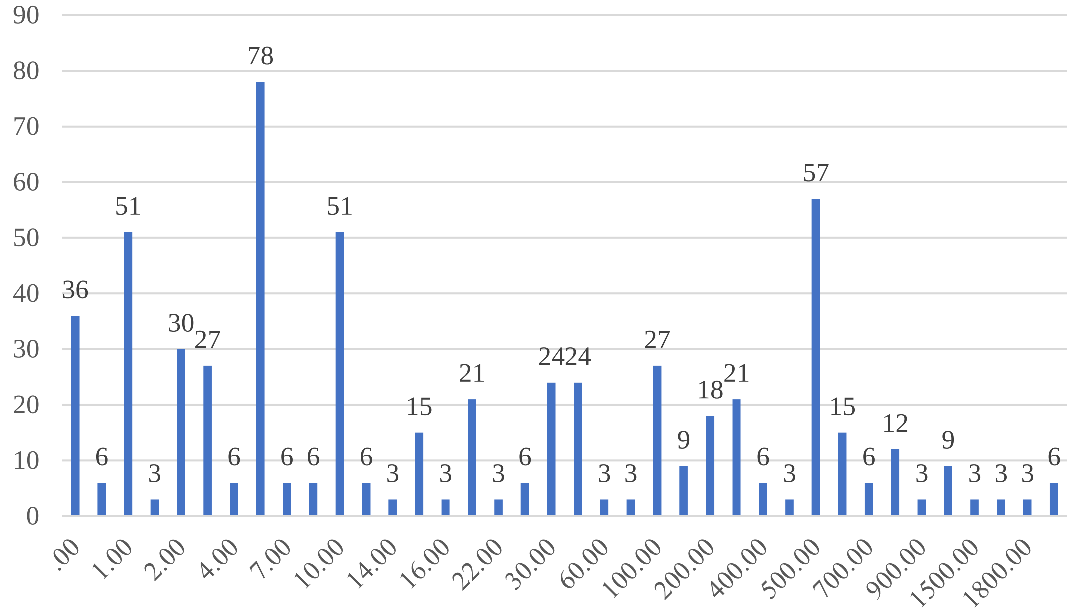


Figure 21 Frequency of walking distance from home to car park or bus stop (m.)

From Table 16 and Figure 21, the walking distance from home to car park or bus stop ranged from 0 – 2,000 meters. The highest frequency was 5 meters. The average distance was 183.50 meters.

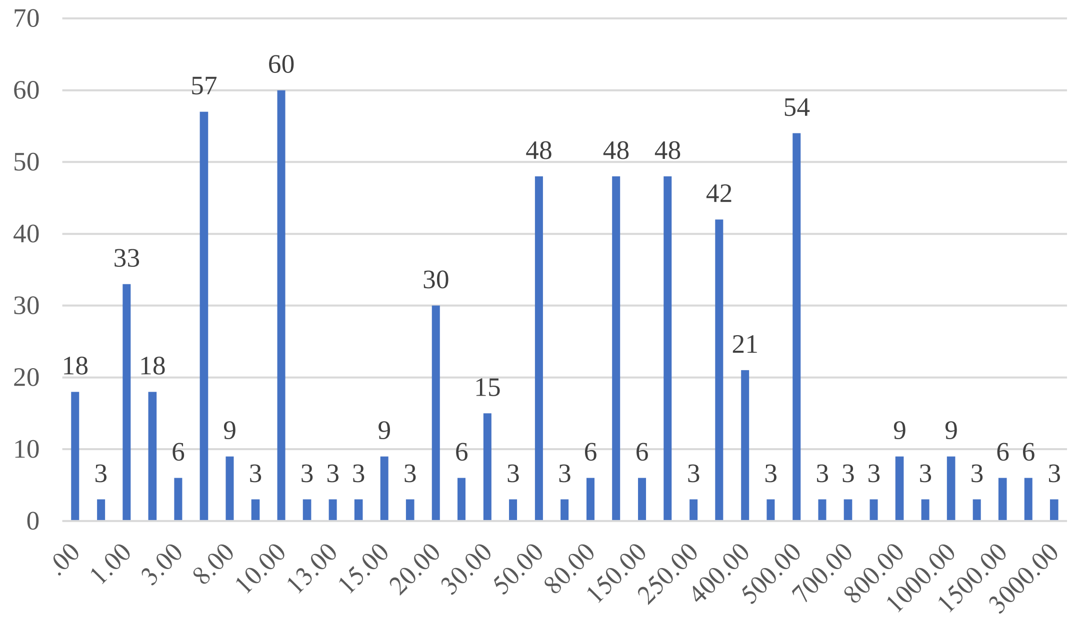


Figure 22 Frequency of walking distance from office / university to car park / bus stop (m.)

From Table 16 and Figure 22, the walking distance from office / university to car park / bus stop ranged from 0 – 3,000 meters. The highest frequency was 10 meters. The average distance was 212.09 meters.

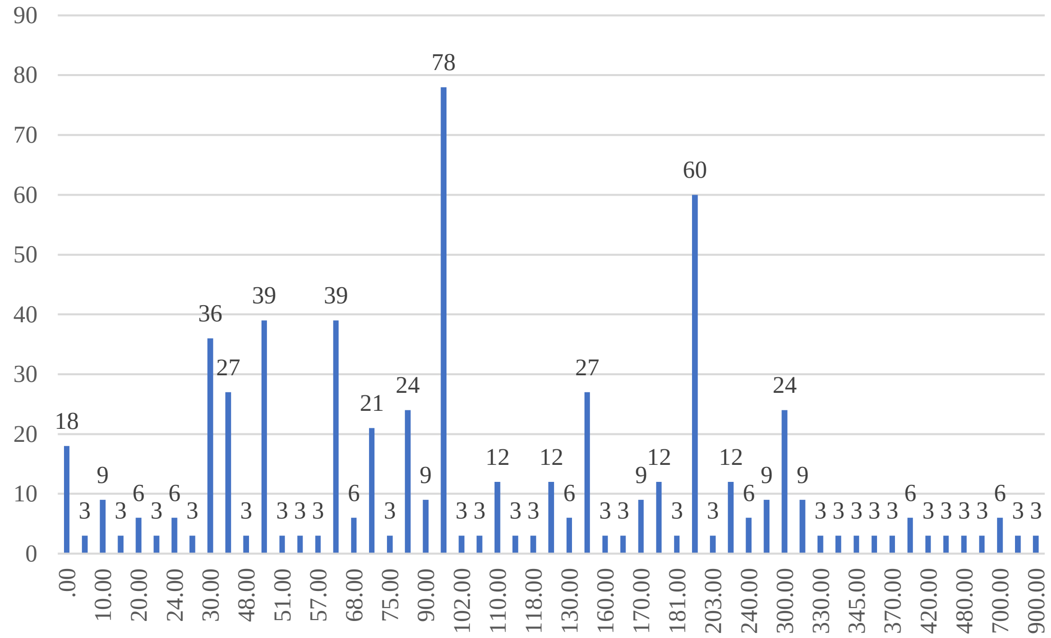


Figure 23 Frequency of daily travel cost (Baht)

From Table 16 and Figure 23, the daily travel cost ranged from 0 – 900 Baht. The highest frequency was 100 Baht. The average travel cost was 139.92 Baht.

4.1.2.3 Ride hailing experience and using characteristics

As shown in Table 17, The majority of the respondents had an experience of using ride-hailing services or mobile-app taxis (79.9%), only 20.1% had never used the service. For those who had experience using ride-hailing services, most of them use less than once a month (65.7%), for work or study purpose (35.8%). The average total cost of using was 111.65 Baht.

Table 17 Ride hailing experience and using characteristics

Attribute		Frequency	Percentage
Ride hailing experience	Yes	489	79.9
	No	123	20.1
Frequency of using ride hailing per month	Never used	123	20.1
	Less than once	402	65.7
	1-2 times	30	4.9
	3-4 times	18	2.9
	More than 4 times	39	6.4
Travel purpose	Never used	123	20.1
	Work or study	219	35.8
	Visit friends or family	33	5.4
	Travel or relax	72	11.8
	Shopping	93	15.2
	Visit doctor	33	5.4
	Other	39	6.4
Cost	$\bar{x}$ = 111.65, S.D. = 97.56		

4.1.2.4 Car-sharing awareness and experience

From Table 18, most of the respondents (62.3%) were unaware of car sharing, and only 8.8% of the respondents had experienced car-sharing services.

Table 18 Car-sharing awareness and experience

		Frequency	Percentage
Know car-sharing	Yes	231	37.7
	No	381	62.3
Car-sharing experience	Yes	54	8.8
	No	558	91.2

4.1.2.5 Intention to use car sharing

When the respondents were asked about expected purpose for using car-sharing, most of them decided to use car sharing for work or study (45.1%), followed by travel or relax (27.9%), and shopping (10.3%), respectively. The majority of the respondents indicated that they will use car-sharing to replace the current mode of travel (39.7%), while one third of them tended to use car sharing to connect other mode of transport (33.3%). An average acceptable longest walking distance from car-sharing station to their home or workplace was 458.98 meters, and an acceptable longest waiting time for shared-car availability was 19.52 minutes. The results of car sharing preference are shown in Table 19.

Table 19 Car sharing preference

		Frequency	Percentage
Expected purpose of using car-sharing	Work or study	276	45.1
	Visit friends or family	39	6.4
	Travel or relax	171	27.9
	Shopping	63	10.3
	Visit doctor	60	9.8
	Other	3	0.5
Expected activity of using car-sharing	Replace current mode	243	39.7
	Use for travel during the day	147	24.0
	Use for connecting to other modes	204	33.3
	Others	18	2.9
Acceptable longest walking distance (m.)	$\bar{x}$ = 458.98, S.D. = 847.71		
Acceptable longest waiting time (minute)	$\bar{x}$ = 19.52, S.D. = 12.01		

Probability of using car sharing

The respondents were asked about the probability of using car sharing which ranking from 0 (Absolutely not using car sharing) to 100 (Definitely use car sharing). The results show in Table 20 and Figure 24, 22.2% of the respondents answered that they will 50% probably use car sharing, about 17.2% were definitely not using car-sharing, and 6.2% will definitely use car sharing. The results indicated that most people are reluctant to use the new service.

Table 20 Probability of using car sharing

Probability	**Frequency**	**Percentage**
0.00	105	17.2
1.00	1	0.2
5.00	6	1.0
10.00	25	4.1
20.00	38	6.2
25.00	1	0.2
30.00	38	6.2
35.00	2	0.3
40.00	52	8.5
45.00	3	0.5
50.00	136	22.2
55.00	4	0.7
60.00	50	8.2
65.00	4	0.7
70.00	41	6.7
72.00	1	0.2
75.00	3	0.5
79.00	1	0.2
80.00	51	8.3
90.00	12	2.0
100.00	38	6.2
Total	**612**	**100.0**

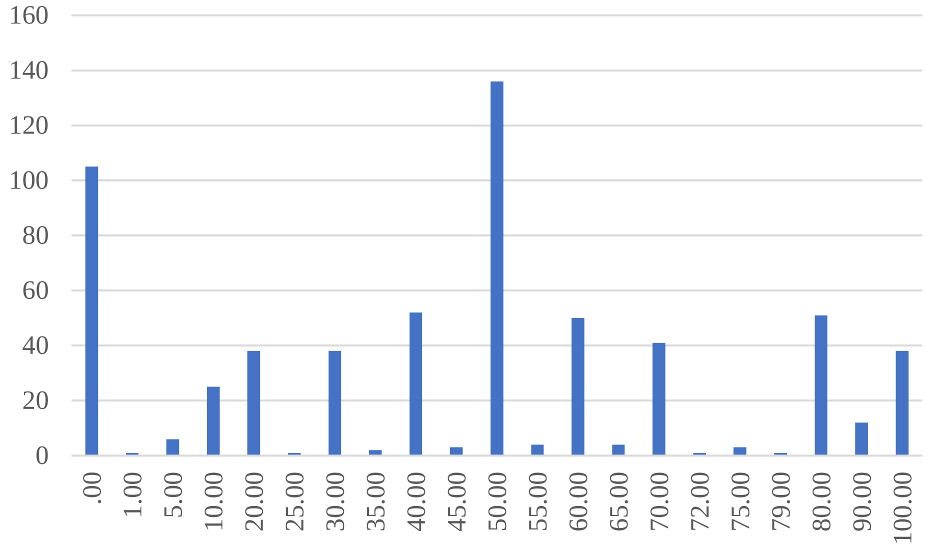


Figure 24 Probability of using car sharing

4.1.3 Mean Difference Test

The purpose of this section is to compare the probability of using car sharing in the group of dependent variables. There were thirteen categorical variables, which can be categorized into two types. The first type was the variables with two groups, including gender, driving license holding, car-sharing awareness, car-sharing experience, and ride-hailing experience. T-test analysis was applied to this group to examine the mean difference. In addition, the variables with more than two groups, including age, employment status, personal monthly income, mode of travel, travel purpose, frequency of using ride-hailing, purpose of using ride hailing, expected activity for use of car sharing and expected reason of using car sharing were analyzed with one-way ANOVA in order to find the mean difference between groups. If a difference was found, then a post-hoc test was performed to examine which pairs of means were statistically significant. A summary of mean comparisons is shown in Table 21.

Table 21 Mean comparison

Variable		**$\bar{x}$**	**S.D.**	**Sig.**
Gender	Male	-0.498	2.47	0.392
	Female	-0.688	2.74	
Age	18-20	-0.484	0.79	0.001*
	21-40	-0.364	2.61	
	41-60	-1.199	2.72	
	More than 60	-2.419	2.31	
Employment status	Student	-0.238	2.50	0.031*
	Freelance	-0.334	2.16	
	Full time	-0.592	2.73	
	Part time	-0.938	2.59	
	Retired / Unemployed	-1.545	2.64	

Table 21 (continue)

Variable		$\bar{x}$	S.D.	Sig.
Personal monthly income (Thai Baht)	Less than 20,000	-0.640	2.79	0.217
	20,000 – 40,000	-0.772	2.67	
	40,001 – 60,000	-0.691	2.19	
	More than 60,000	-0.035	2.60	
Driving license holder	Yes	-0.579	2.578	0.551
	No	-0.722	2.803	
Mode of travel	Private car (as a driver)	-0.429	2.54	0.017*
	Private car (as a passenger)	-1.404	2.66	
	Public transport	-0.643	2.74	
Travel purpose	Working/studying	-0.543	2.69	0.042*
	Visiting friends or relatives	-1.811	1.56	
	Traveling/relaxing	0.251	1.85	
	Shopping	-1.408	1.96	
	Visiting doctor	-2.212	3.39	
Ride hailing experience	Yes	-0.380	2.576	0.000*
	No	-1.565	2.688	
Frequency of using ride-hailing per month	Never	-1.565	2.69	0.000*
	Less than once	-0.464	2.58	
	1-2 times	1.023	2.93	
	3-4 times	-0.839	2.10	
	More than 4 times	-0.385	2.11	
Purpose of using ride-hailing	Never	-1.565	2.69	0.000*
	Working/studying	-0.343	2.53	
	Visiting friends or relatives	0.440	1.77	
	Traveling/relaxing	-0.496	2.84	
	Shopping	-0.123	2.15	
	Visiting doctor	-0.368	3.30	
	Others	-1.694	2.80	
Car-sharing awareness	Yes	-0.430	2.775	0.169
	No	-0.732	2.551	
Car-sharing experience	Yes	1.003	2.114	0.000*
	No	-0.775	2.63	
Expected activity of using car sharing	Working/studying	-0.090	2.63	0.000*
	Visiting friends or relatives	-0.806	2.76	
	Traveling/relaxing	-1.129	2.62	
	Shopping	-1.008	2.22	
	Visiting doctor	-0.877	2.60	
	Others	-4.246	1.81	

Table 21 (continue)

Variable		$\bar{x}$	S.D.	Sig.
Expected reason of using car-sharing	For replacing current mode	-0.1521	2.55	0.000*
	For traveling during the day	-0.5975	2.47	
	For connecting to other modes of transport	-0.8758	2.67	
	Others	-4.1759	1.55	

* is statistically significant at 0.05 level

Table 21 shows mean differences were found with ten variables: age, occupation, mode of travel, travel purpose, ride-hailing experience, ride-hailing monthly frequency, purpose of using ride-hailing, car-sharing experience, intended activity of using car sharing and intended reason of using car sharing. A further step was to examine which particular differences between pairs of means were significant using Scheffe analysis. The details of mean comparison between pairs are as follows.

4.1.3.1 Gender

Table 22 shows the probability of using car sharing between male and female with means of -0.498 and -0.688, respectively. The t-test analysis revealed a t-value of 0.856, and a p-value of 0.392. Therefore, there is no significant difference between the probability of using carsharing based on gender.

Table 22 t-test analysis based on gender

Probability	Male		Female		T-value	P-value
	$\bar{x}$	S.D.	$\bar{x}$	S.D.		
Probability of using car sharing	-0.498	2.47	-0.688	2.74	0.856	0.392

4.1.3.2 Age

Table 23 shows one-way ANOVA analysis associated with the probability of using car sharing by age. The analysis indicated the F-value of 5.449 and P-value of 0.001. Therefore, there was significant a difference between the probability of using car sharing based on age group.

Table 23 One-way ANOVA analysis based on age

Probability	F-value	P-value
Probability of using car sharing	5.449	0.001*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 24 shows the Scheffe analysis for the different age groups. One pair was statistically different, in that people aged 21-40 were found to be more likely to use car sharing than the people who are aged 41-60.

Table 24 Scheffe analysis for the different age groups

Age	$\bar{x}$	18-20	21-40	41-60	More than 60
18-20	-0.484	-	-0.119	0.715	1.935
21-40	-0.364		-	0.834*	2.055
41-60	-1.199			-	1.220
More than 60	-2.419				-

* is statistically significant at 0.05 level

4.1.3.3 Occupation

Table 25 shows one-way ANOVA analysis associated with the probability of using car sharing by occupation. The analysis indicated the F-value of 2.686 and P-value of 0.031. Therefore, there was a significant difference between the probability of using car sharing based on occupation group.

Table 25 One-way ANOVA analysis based on occupation

Probability	F-value	P-value
Probability of using car sharing	2.686	0.031*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 26 shows the Scheffe analysis for the different occupation groups. The results reveal that there was no significant difference between occupation groups.

Table 26 Scheffe analysis for the different occupation groups

Occupation	$\bar{x}$	Student	Freelance	Full time	Part time	Retired/Unemployed
Student	-0.238	-	0.096	0.353	0.699	1.306
Freelance	-0.334		-	0.257	0.603	1.210
Full time	-0.592			-	0.346	0.953
Part time	-0.938				-	0.607
Retired/Unemployed	-1.545					-

4.1.3.4 Personal monthly income

Table 27 shows one-way ANOVA analysis associated with the probability of using car sharing by personal monthly income. The analysis indicated the F-value of 1.488 and P-value of 0.217. Therefore, there was no significant difference between the probability of using car sharing based on personal-monthly-income group.

Table 27 One-way ANOVA analysis based on personal monthly income

Probability	F-value	P-value
Probability of using car sharing	1.488	0.217

4.1.3.5 Driving license holder

Table 28 shows the probability of using car sharing between driving license holders and non- driving license holders with means of -0.579 and -0.722, respectively. The t-test analysis revealed a t-value of -0.596, and a p-value of 0.551. Therefore, there was no significant difference between the probability of using car sharing based on driving license holders and non- driving license holders.

Table 28 t-test analysis based on driving license holding

Probability	Yes		No		T-value	P-value
	$\bar{x}$	S.D.	$\bar{x}$	S.D.		
Probability of using car sharing	-0.579	2.578	-0.722	2.803	-0.596	0.551

4.1.3.6 Mode of travel

Table 29 shows one-way ANOVA analysis associated with the probability of using car sharing by mode of travel. The analysis indicated the F-value of 4.079 and P-value of 0.017. Therefore, there was a significant difference between the probability of using car sharing based on mode-of-travel group.

Table 29 One-way ANOVA analysis based on mode of travel

Probability	F-value	P-value
Probability of using car sharing	4.073	0.017*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 30 shows the Scheffe analysis for the different age groups. One pair was statistically different, namely people who drive a private car were more likely to use car-sharing than the people who are a passenger of a private car.

Table 30 Scheffe analysis for the different mode-of-travel groups

Mode of travel	$\bar{x}$	Private car (driver)	Private car (passenger)	Public transport
Private car (Driver)	-0.429	-	0.974*	0.213
Private car (Passenger)	-1.404		-	-0.760
Public transport	-0.643			-

* is statistically significant at 0.05 level

4.1.3.7 Travel purpose

Table 31 shows one-way ANOVA analysis associated with the probability of using car sharing by travel purpose. The analysis indicated the F-value of 4.079 and P-value of 0.017. Therefore, there was a significant difference between the probability of using car sharing based on travel-purpose group.

Table 31 One-way ANOVA analysis based on travel purpose

Probability	F-value	P-value
Probability of using car sharing	2.486	0.042*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 32 shows the Scheffe analysis for the different travel-purpose groups. The result reveals that there was no significant different between travel-purpose groups.

Table 32 Scheffe analysis for the different travel-purpose groups

Travel purpose	$\bar{x}$	Working/studying	Visiting friends or relatives	Traveling/relaxing	Shopping	Visiting doctor
Working/studying	-0.543	-	1.267	-0.795	0.865	1.668
Visiting friends or relatives	-1.811		-	-2.062	-0.402	0.401
Traveling/relaxing	0.251			-	1.660	2.463
Shopping	-1.408				-	0.803
Visiting doctor	-2.212					-

4.1.3.8 Ride-hailing experience

Table 33 shows the probability of using car sharing between people who have ride-hailing experience and non- ride-hailing experience with means of -0.380 and -1.565, respectively. The t-test analysis revealed a t-value of -4.407, and a p-value of 0.000. Therefore, there was a significant difference between the probability of using car sharing based on ride-hailing experience. In greater details, people who had ride-hailing experience were found to be more likely to use car-sharing than the people who had never used ride hailing.

Table 33 t-test analysis based on ride-hailing experience

Probability	Yes		No		T-value	P-value
	$\bar{x}$	S.D.	$\bar{x}$	S.D.		
Probability of using car sharing	-0.380	2.576	-1.565	2.688	-4.407	0.000*

* is statistically significant at 0.05 level

4.1.3.9 Frequency of using ride-hailing

Table 34 shows one-way ANOVA analysis associated with the probability of using car sharing by frequency of using ride-hailing. The analysis indicated the F-value of 7.627 and P-value of 0.000. Therefore, there was a significant difference between the probability to use car-sharing based on frequency-of-using-ride-hailing groups.

Table 34 One-way ANOVA analysis based on ride-hailing monthly frequency usage

Probability	F-value	P-value
Probability of using car sharing	7.627	0.000*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 35 shows the Scheffe analysis for the different group of frequency of using ride-hailing. Two pairs were statistically different, in those people who use ride hailing less than once a month and 1-2 times a month were found to be more likely to use car sharing than people who had never used ride hailing.

Table 35 Scheffe analysis for the different group of frequency of using ride-hailing

Ride-hailing monthly frequency usage	$\bar{x}$	Never	Less than once	1-2 times	3-4 times	More than 4 times
Never	-1.565	-	-1.101*	-2.588*	-0.726	-1.180
Less than once	-0.464		-	-1.487	0.375	-0.079
1-2 times	1.023			-	1.862	1.408
3-4 times	-0.839				-	-0.454
More than 4 times	-0.385					-

4.1.3.10 Purpose of using ride-hailing

Table 36 shows one-way ANOVA analysis associated with the probability of using car sharing by purpose of using ride hailing. The analysis indicated the F-value of 5.893 and P-value of 0.000. Therefore, there was a significant difference between the probability to use car-sharing based on purpose-of-using-ride-hailing groups.

Table 36 One-way ANOVA analysis based on purpose of using ride hailing

Probability	F-value	P-value
Probability to use car-sharing	5.893	0.000*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 37 shows the Scheffe analysis for the different group of purpose of using ride-hailing. One pair was statistically different, in that people who use ride hailing for working or studying were found to be more likely to use car sharing than the people who had never used ride-hailing service.

Table 37 Scheffe analysis for the different group of purpose of using ride hailing

Travel purpose	$\bar{x}$	Never	Working/ studying	Visiting friends or relatives	Traveling/relaxing	Shopping	Visiting doctor	Others
Never	-1.565	-	-1.22*	-2.00	-1.06	-1.44	-1.19	0.12
Working/studying	-0.343		-	-0.78	0.15	-0.21	0.02	1.35
Visiting friends or relatives	0.440			-	0.94	0.56	0.80	2.13
Traveling/relaxing	-0.496				-	-0.37	-0.12	1.19
Shopping	-0.123					-	0.24	1.57
Visiting doctor	-0.368						-	1.32
Others	-1.694							-

* is statistically significant at 0.05 level

4.1.3.11 Car-sharing awareness

Table 38 shows the probability of using car sharing between people who aware of car sharing and people who are unaware of car sharing with means of -0.430 and -0.732, respectively. The t-test analysis revealed a t-value of -1.375, and a p-value of 0.169. Therefore, there was no significant difference between the probability of using car sharing based on car-sharing-awareness groups.

Table 38 t-test analysis based on car sharing awareness

Probability	Yes		No		T-value	P-value
	$\bar{x}$	S.D.	$\bar{x}$	S.D.		
Probability of using car sharing	-0.430	2.775	-0.732	2.551	-1.375	0.169

4.1.3.12 Car-sharing experience

Table 39 shows the probability of using car sharing between people who have car-sharing experience and non-car-sharing experience with means of 1.003 and -0.775, respectively. The t-test analysis revealed a t-value of -4.814, and a p-value of 0.000. Therefore, there was a significant difference between the probability to use car-sharing based on car-sharing experience. In greater details, people experiencing car sharing were found to be more likely to use car sharing than the people who had never used car sharing.

Table 39 t-test analysis based on car sharing awareness

Probability	Yes		No		T-value	P-value
	$\bar{x}$	S.D.	$\bar{x}$	S.D.		
Probability of using car sharing	1.003	2.114	-0.775	2.63	-4.814	0.000*

* is statistically significant at 0.05 level

4.1.3.13 Expected activity of using car-sharing

Table 40 shows one-way ANOVA analysis associated with the probability of using car sharing by expected activity of using car sharing. The analysis indicated the F-value of 5.224 and P-value of 0.000. Therefore, there was a significant difference between the probability of using car sharing based on ecpected-activity-of-using-car-sharing groups.

Table 40 One-way ANOVA analysis based on expected activity of using car sharing

Probability	F-value	P-value
Probability of using car sharing	5.224	0.000*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 41 shows the Scheffe analysis for the different group of expected activity of using car sharing. One pair was statistically different, namely people who will use car sharing for working or studying were found to be more likely to use car sharing than people who will use car sharing for traveling or relaxing.

Table 41 Scheffe analysis for the different group of expected activity of using car sharing

Expected activity	$\bar{x}$	Working / studying	Visiting friends or relatives	Traveling / relaxing	Shopping	Visiting doctor	Others
Working / studying	-0.090	-	0.715	1.038*	0.917	0.786	4.155
Visiting friends or relatives	-0.806		-	0.323	0.202	0.071	3.440
Traveling / relaxing	-1.129			-	-0.121	-0.252	3.117
Shopping	-1.008				-	-0.131	3.238
Visiting doctor	-0.877					-	3.369
Others	-4.246						-

* is statistically significant at 0.05 level

4.1.3.14 Expected reason of using car-sharing

Table 42 shows One-way ANOVA analysis associated with the probability of using car sharing by expected reason of using car sharing. The analysis indicates the F-value of 15.041 and P-value of 0.000. Therefore, there was a significant difference between the probability of using car sharing based on expected-reason-of-using-car-sharing groups.

Table 42 One-way ANOVA analysis based on expected reason of using car sharing

Probability	F-value	P-value
Probability of using car sharing	15.041	0.000*

* is statistically significant at 0.05 level

Then, a post-hoc test was used to find out which pairs of mean were significant. Table 43 shows the Scheffe analysis for the different group of expected reason of using car sharing. Four pair were statistically different. Firstly, people who will use car sharing for replacing the current mode of travel were more likely to use car sharing than the people who will use car sharing for connecting other modes of transport and other reasons. In addition, people who will use car sharing for travel during the day were more likely to use car-sharing than the people who will use car sharing for other reasons, and people who will use car sharing for connecting other modes of transport are more likely to use car-sharing than the people who will use car sharing for other reasons.

Table 43 Scheffe analysis for the different group of expected activity of using car sharing

Age	$\bar{x}$	Replacing	Traveling during the day	Connecting	Others
Replacing	-0.152	-	0.445	0.723*	4.023*
Traveling during the day	-0.597		-	0.278	3.578*
Connecting	-0.875			-	3.300*
Others	-4.175				-

* is statistically significant at 0.05 level

4.1.4 Regression Analysis

Multiple linear regression analysis was performed in order to understand the significant factors influencing car-sharing adoption. There were three groups of independent variables: socio-economic status, travel behavior and car-sharing preference. The dependent variable was the probability of using car-sharing, which was transformed to log odds.

As shown in Table 44, the data were categorized into two types: (1) categorical data, which were transformed to a dummy variable, and (2) scale data, which could be used for the analysis directly without transforming. Also, the variables with the star were the reference groups for the multiple linear regression analysis.

Table 44 Variables used in the multiple linear regression analysis

Variable	Description	Data type
Socio-economics		
Gender	Male	Categorical data
	Female*	
Age	18-21 *	Categorical data
	21-30	
	31-40	
	Above 40	
Employment status	Student*	Categorical data
	Freelance / Own business	
	Full time	
	Part time	
	Unemployed or retired	
Personal monthly income (Thai Baht)	Under 20,000 *	Categorical data
	20,000-40,000	
	40,001-60,000	
	Above 60,000	
Number of residents in a household		Scale
Number of owned private cars		Scale
Driving license holding	Yes / No	Categorical data
Travel Behavior		
Mode of travel	Private car as a driver*	Categorical data
	Private car as a passenger	
	Public transport	
Weekly travel frequency	No. of days travelling in a week	Scale
Number of fellows	No. of accompany	Scale
Travel purpose	For working or studying*	Categorical data
	For visiting friends or relatives	
	For traveling or relaxing	
	For shopping	
	For visiting a doctor	
Average daily trip distance		Scale
Average daily trip duration		Scale
Walking distance from home to car park or bus stop		Scale
Walking distance from office / university to car park or bus stop		Scale
Average daily trip expense		Scale
Ride-hailing experience	Yes / No	Categorical data
Car-sharing awareness	Yes / No	Categorical data
Car-sharing experience	Yes / No	Categorical data

Table 44 (Continue)

Variable	Description	Data type
Car-sharing preference		
Expected activity for using car sharing	For working or studying*	Categorical data
	For visiting friends or relatives	
	For traveling or relaxing	
	For shopping	
	For visiting a doctor	
	Others	
Expected reason of using car sharing	For replacing current mode*	Categorical data
	For traveling during the day	
	For connecting to other modes of transport	
	Other reasons	
Acceptable longest walking distance to car-sharing station		Scale
Acceptable longest waiting time for shared car availability		Scale
Price	100 Baht/hour + 60 Baht of fuel price	Scale
	120 Baht/hour + 60 Baht of fuel price	
	140 Baht/hour + 60 Baht of fuel price	

* is the reference category used in the linear regression model

4.1.4.1 Multicollinearity

In order to obtain valid and reliable data analysis, the data collection process was carefully checked for potential problems of multicollinearity between independent variables. Before performing multiple linear regression analysis, the collinearity statistics, including tolerance scores and the variation inflation factor (VIF), were tested (Table 45).

Table 45 Multicollinearity analysis

Variable	Collinearity Statistics	
	Tolerance	**VIF**
Male	0.695	1.439
Age: 20-40	0.087	11.456
Age: 41-60	0.083	12.069
Age: More than 60	0.422	2.372
Employment status: Freelance / Own business	0.365	2.739
Employment status: Full time	0.230	4.357
Employment status: Part-time	0.675	1.481
Employment status: Unemployed	0.408	2.452
Income: 20,000-40,000 Baht	0.420	2.380
Income: 40,001-60,000 Baht	0.454	2.202
Income: Above 60,000 Baht	0.408	2.449
Number of residents in a household	0.704	1.421
Number of owned private cars	0.536	1.865

Table 45 (continue)

Variable	Collinearity Statistics	
	Tolerance	VIF
Driving license holding	0.519	1.927
Car-sharing awareness	0.699	1.431
Car-sharing experience	0.630	1.586
Travel mode: Private car as a passenger	0.588	1.699
Travel mode: Public transport	0.392	2.550
Weekly travel frequency	0.548	1.824
Number of fellows	0.696	1.437
Travel purpose: For visiting friends or relatives	0.779	1.284
Travel purpose: For traveling or relaxing	0.680	1.470
Travel purpose: For shopping	0.647	1.546
Travel purpose: For visiting a doctor	0.666	1.501
Travel distance	0.619	1.616
Travel duration	0.633	1.579
Walking distance from home to car park or bus stop	0.503	1.989
Walking distance from office / university to car park or bus stop	0.546	1.831
Average daily trip expense	0.597	1.676
Ride-hailing experience	0.694	1.441
Expected activity of using car sharing: For visiting friends or relatives	0.766	1.305
Expected activity of using car sharing: For traveling or relaxing	0.621	1.610
Expected activity of using car sharing: For shopping	0.678	1.476
Expected activity of using car sharing: For visiting a doctor	0.635	1.576
Expected activity of using car sharing: Others	0.704	1.420
Expected reason of using car sharing: For traveling during the day	0.605	1.653
Expected reason of using car sharing: For connecting to other modes of transport	0.554	1.806
Expected reason of using car sharing: Other reasons	0.602	1.660
Acceptable longest walking distance to car-sharing station	0.711	1.407
Acceptable longest waiting time for shared car availability	0.805	1.242
Price	1.000	1.000

Dependent Variable: LNY

From Table 45, the results from the collinearity statistics between variables showed that there were multicollinearity problems between age variables as the tolerance scores for age 20-40 and 41-60 were below 0.2 and VIF scores above 10

(Saunders, Lewis, & Thornhill, 2009). Therefore, the age variables were deleted and tested the multicollinearity between variables again. Table 46 shows the collinearity statistics after removing the age variables. The Table 46 indicated the collinearity statistics after removed the variables of age.

Table 46 Multicollinearity analysis after removed age variables

Variable	**Collinearity Statistics**	
	Tolerance	**VIF**
Male	0.706	1.417
Employment status: Freelance / Own business	0.404	2.474
Employment status: Full time	0.264	3.789
Employment status: Part-time	0.705	1.419
Employment status: Unemployed	0.459	2.177
Income: 20,000-40,000 Baht	0.481	2.079
Income: 40,001-60,000 Baht	0.491	2.035
Income: Above 60,000 Baht	0.453	2.208
Number of residents in a household	0.711	1.407
Number of owned private cars	0.539	1.855
Driving license holding	0.524	1.907
Car-sharing awareness	0.703	1.423
Car-sharing experience	0.632	1.583
Travel mode: Private car as a passenger	0.606	1.650
Travel mode: Public transport	0.395	2.531
Weekly travel frequency	0.552	1.811
Number of fellows	0.752	1.329
Travel purpose: For visiting friends or relatives	0.783	1.277
Travel purpose: For traveling or relaxing	0.694	1.442
Travel purpose: For shopping	0.672	1.488
Travel purpose: For visiting a doctor	0.669	1.495
Travel distance	0.628	1.594
Travel duration	0.637	1.571
Walking distance from home to car park or bus stop	0.526	1.902
Walking distance from office / university to car park or bus stop	0.557	1.796
Average daily trip expense	0.600	1.667
Ride-hailing experience	0.718	1.393
Expected activity of using car sharing: For visiting friends or relatives	0.772	1.296
Expected activity of using car sharing: For traveling or relaxing	0.648	1.542
Expected activity of using car sharing: For shopping	0.685	1.459
Expected activity of using car sharing: For visiting a doctor	0.674	1.484
Expected activity of using car sharing: Others	0.722	1.385

Table 46 (continue)

Variable	Collinearity Statistics	
	Tolerance	VIF
Expected reason of using car sharing: For traveling during the day	0.612	1.634
Expected reason of using car sharing: For connecting to other modes of transport	0.556	1.798
Expected reason of using car sharing: Other reasons	0.619	1.615
Acceptable longest walking distance to car-sharing station	0.764	1.309
Acceptable longest waiting time for shared car availability	0.809	1.237
Price	1.000	1.000

Dependent Variable: LNY

After deleting age variables and testing the multicollinearity again, the results from the collinearity statistics between variables revealed that there was no multicollinearity problem between variables as the tolerance scores in all cases above 0.2 and VIF score below 10 (Saunders et al., 2016). Therefore, there were separate effects of variables in the course of further data analysis.

4.1.4.2 Multiple linear regression analysis

In this study, multiple linear regression analysis was used to investigate the factors influencing the likelihood of using car sharing in Bangkok. The data was analyzed using the statistical software program, IBM SPSS Statistics 21.

The multiple linear regression analysis was run with the variables in Table 44, except age variables. The adjusted R^2, which indicates the percent of how much of the total variance is explained by the independent variables, was 23.7% (Table 47). Table 48 shows the analysis of variance for multiple regression showed that independent variables significantly predicted the probability to use car-sharing among the sample surveyed ($F = 5.982$, $p<0.05$).

Table 47 Model summary

Model	R	R Square	Adjusted R Square	Std.Error of the Estimate
1	0.533	0.284	0.237	2.30677

Dependent Variable: LNY

Table 48 Analysis of variance - ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1209.613	38	31.832	5.982	.000[b]
Residual	3049.047	573	5.321		
Total	4258.660	611			

The results of the multiple linear regression analysis were shown in Table 49. Twelve variables were statistically significant, including modes of travel, travel purpose, walking distance, ride-hailing experience, car-sharing experience, expected purpose for using car-sharing, expected reasons to use car-sharing, acceptable longest waiting time for a shared-car availability, and the price of the service. Table 50 shows the marginal effects which indicate the magnitude and types of association between the explanatory variables on the probability of the response variable (Zelalem, 2014) The interpretation of each variable is as follows:

(1) Socio-economic status of the respondents did not affect the probability of using car-sharing.

(2) Mode of travel has a significant influence on the probability to use car-sharing. The mode of travel of private car (as a passenger) and public transport has a negative coefficient. In other words, the people who travel by private car (as a passenger), and use both private car and public transport are less likely to use car-sharing than the people who drive, approximately 27.75% and 16.0%, respectively.

(3) The traveling purpose affected the decision to use car-sharing. The people who traveled for shopping were 14.8% less likely to use shared car, compared with people who traveled for work or study.

(4) The walking distance, both from home to car park or bus stop and the return trip, was significant to the customers' intention to use car-sharing. The longer walking distance, the higher probability to use car-sharing.

(6) The experience of using ride-hailing service was significant, with positive coefficient and AME 19.1%. It revealed that the people who had the ride-hailing experience (or mobile-app taxi) were about 19.1% more likely to choose car-sharing.

(7) The experience of using car-sharing has a positive significant influence the intention to use car-sharing, with average marginal effects (AME) 27.2%. It could be interpreted that with the experience of using car-sharing, the probability of choosing car-sharing increase by 27.2%.

(8) The expected activity of using car-sharing was significant in relation to the propensity to use car-sharing. The people who were likely to use car-sharing for travel or relaxation were found to be approximately 14.0% less likely to choose car-sharing than the people who tend to use car-sharing for work or study.

(9) The expected reasons of using car-sharing had a significant impact on the customers' decision to use the service. Those people who would use car-sharing for connecting to other modes of transport, and other reasons, such as when they were in hurry or it was raining, were less likely to use car-sharing than the people who would use car-sharing to replace the current mode of transport (11.9% and 59.7%, respectively).

(10) The acceptable longest waiting time for shared car availability was significant in relation to customers' intention to use car-sharing. The people who had more patience to wait were more likely to choose car-sharing.

(11) Price affected the willingness to use car-sharing with a negative coefficient. It can be concluded that the increase in car-sharing service price could reduce the customers' willingness to use it, by approximately 0.46%.

Table 49 Results of the multiple linear regression analysis

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.969	1.022	-	3.885	0.000
Use private car (as a passenger)	-1.724	0.372	-0.211	-4.638	0.000
Use both private car and public transport	-0.998	0.311	-0.180	-3.205	0.001
Travel for shopping for daily life	-0.919	0.450	-0.088	-2.042	0.042
Distance from home to car park or bus stop	0.001	0.000	0.102	2.092	0.037
Distance from office to car park or bus stop	0.001	0.000	0.126	2.656	0.008
Ride-hailing experience	1.192	0.275	0.181	4.341	0.000
Car-sharing experience	1.692	0.414	0.182	4.091	0.000
Use car-sharing for travel or relaxing	-0.875	0.258	-0.149	-3.391	0.001
Use car-sharing for connecting other modes	-0.741	0.265	-0.132	-2.793	0.005
Use car-sharing for other reasons	-3.718	0.701	-0.238	-5.301	0.000
Acceptable longest waiting time for a shared car	0.024	0.009	0.109	2.774	0.006
Price	-0.029	0.006	-0.177	-5.017	0.000

Table 50 Marginal effect of each variable

Variable	**Marginal Effects ($\frac{dy}{dx}$)**		
	Average	**Max**	**Min**
Use private car (as a passenger)	-0.277	-0.009	-0.431
Use both private car and public transport	-0.160	-0.005	-0.250
Travel for shopping for daily life	-0.148	-0.005	-0.230
Distance from home to car park or bus stop	0.000	0.000	0.000
Distance from office to car park or bus stop	0.000	0.000	0.000
Ride-hailing experience	0.191	0.298	0.006
Car-sharing experience	0.272	0.423	0.008
Use car-sharing for travel or relaxing	-0.140	-0.004	-0.219
Use car-sharing for connecting other modes	-0.119	-0.004	-0.185
Use car-sharing for other reason	-0.597	-0.018	-0.930
Acceptable longest waiting time for a shared car	0.003853	0.006	0.000119
Price	-0.00466	-0.00014	-0.00725

4.2 Results of study two

4.2.1 Data

As described in Chapter 3, the survey was conducted through online questionnaires and distributed in public places such as bus stops, shopping malls, offices, and universities. The target group was selected by age older than 18 years old living, studying, or working in Bangkok. In total, 505 participants completed the questionnaire.

4.2.2 Descriptive statistics

The characteristics of respondents are shown in Table 51. It can be seen that the proportion of females (64.20%) was higher than males (35.80%). The majority of the respondents was in the age range 20-40, which was considered the target group for car-sharing services. The main employment status was full-time staff (39.80%), followed by students (31.0%), business owners or freelance (21.60%), retired or unemployed (4.80%), and part time (2.80%). Personal monthly income was mainly concentrated in less than 20,000 Baht group (46.90%). Most of the respondents owned one car. Most of the respondents commute by driving private car (51.50%). The majority of the respondents had never experienced car sharing (89.70%).

Table 51 Socio-economic status of the respondents

Socio-economic status		Frequency	Percentage
Gender	Male	181	35.80
	Female	324	64.20
Age	18 - 20	62	12.30
	20 – 40	325	64.40
	41 - 60	94	18.60
	More than 60	24	4.80
Employment status	Students	157	31.0
	Business owner / Freelance	109	21.60
	Full time	201	39.80
	Part time	14	2.80
	Retired / Unemployed	24	4.80
Personal monthly income (Thai Baht)	Less than 20,000	237	46.90
	20,000 – 40,000	190	37.60
	40,001 – 60,000	55	10.90
	More than 60,000	23	4.60
Number of owned private cars	None	165	32.70
	1 car	242	47.90
	2 cars	67	13.30
	3 cars	23	4.60
	More than 3 cars	8	1.60

Table 51 (continued)

Socio-economic status		Frequency	Percentage
Mode of travel	Private car (as a driver)	260	51.50
	Private car (as a passenger)	90	17.80
	Public transport	84	16.60
	Both private car and public transport	71	14.10
Car sharing experience	Yes	52	10.30
	No	453	89.70

The questionnaire comprised eight constructs and 49 items. The respondents rated statements based on their opinions. Mean and standard deviation of measurement constructs and items are shown in Table 52. Items were based on the following five Likert scales:

5	=	Strongly agree
4	=	Agree
3	=	Neutral
2	=	Disagree
1	=	Strongly disagree

The interpretation criteria can be defined with the following score range:

4.50 - 5.00	=	Strongly agree
3.50 – 4.49	=	Agree
2.50 – 3.49	=	Neutral
1.50 – 2.49	=	Disagree
1.00 – 1.49	=	Strongly disagree

As shown in Table 52, respondents self-reported that they are innovative and environmentally concerned, with overall average scores of 3.80 and 3.91, respectively. For the social influence factor, the respondents' answers were consistency in agreement that people around them could lead to their decision to use car sharing (Mean = 3.59). While the viewpoint of perceived risks including information risk, operational risk and physical risk, were rated in agree range with means of 3.59, 3.56 and 3.79, respectively. However, the participants agreed that car sharing was useful in terms of cost saving, convenience and economic and social benefits, with average scores of 3.61, 3.74 and 3.58, respectively. Moreover, the respondents' thought that car sharing is easy to use, with the average score of 3.71. Lastly, the respondents' opinions were consistently in agreement with statements indicating a positive attitude toward car sharing and an intention of using car sharing, with average scores of 3.83 and 3.68, respectively.

Table 52 Mean and standard deviation of measurement constructs and items

Construct	Item		Mean	SD
Personal innovativeness (PI)			**3.80**	**0.88**
	I usually try a new mobile-based service such as Grab or Lineman.	PI1	3.60	1.23
	I would not hesitate to try out a new mobile application.	PI2	3.70	1.02
	I am able to understand mobile application quickly.	PI3	4.09	0.98
Environmental concern (EC)			**3.91**	**0.73**
	I am concerned about the world's future environment.	EC1	3.90	1.02
	I think that human consumption today will cause environmental problems in the future.	EC2	4.09	0.89
	I consider the potential environmental impact of my actions when making my decisions.	EC3	3.90	0.85
	I am willing to be inconvenienced in order to take actions that are more environmentally friendly.	EC4	3.73	0.94
Social Influence (SI)			**3.59**	**0.86**
	If my friends or colleagues use car sharing, I will also use car sharing.	SI1	3.60	1.00
	If a member of my family uses car sharing, I will also use car sharing.	SI2	3.60	1.03
	If famous people use car sharing, I will also use car sharing.	SI3	3.43	1.08
	Car sharing advertising will persuade me to use it.	SI4	3.52	1.01
	The reviews of real user will courage the use of car sharing.	SI5	3.78	0.95
Perceived Risk (PR)			**3.69**	**0.70**
	Information risk	PIR	3.59	0.92
	I am concerned that my personal information will be shared or sold to others when enter the car-sharing platform.		3.64	1.03
	I am concerned about unauthorized users gaining access to my account.		3.55	1.06
	Payment method would be unsafe.		3.57	0.99
	Functional risk	PFR	3.56	0.84
	I am afraid of transaction error		3.58	0.92
	The system would be unstable, causing issues with its use.		3.53	0.90

Table 52 (continue)

Construct	Item		Mean	SD
Perceived Risk (PR)			**3.69**	**0.70**
	Physical risk	PPR	3.79	0.73
	I am concerned that a shared-car I want will not be available when I want it.		3.66	0.94
	I am concerned about driving an unfamiliar-shared-car.		3.65	1.00
	I am worried about using shared cars (such as maintenance, cleanliness, etc.).		3.69	0.96
	I am worried about Covid-19 when using shared car.		4.00	0.97
	I am concerned about the safety assurance of car-sharing service in case of an accident.		3.92	0.93
	I am concerned about criminal activity that may occur while using car-sharing service.		3.82	0.90
Perceived Usefulness (PU)			**3.67**	**0.69**
	Cost saving	PUS	3.61	0.79
	Using car sharing can save the cost of car ownership		3.73	0.94
	Using car sharing can save the travel expense		3.60	0.91
	Car sharing is safer than other modes of transportation service.		3.49	0.89
	Convenience	PUC	3.74	0.72
	Using car sharing, I could drive a new car.		3.57	0.89
	Using car sharing, I could choose a car suiting to my traveling purpose.		3.84	0.89
	Using car sharing, I could access and return a shared car at many drop points.		3.79	0.88
	Using car sharing, I could use a shred car when I want to.		3.85	0.88
	Car sharing is convenient and flexible		3.77	0.89
	Car sharing would enable me to get to my destination more quickly.		3.61	0.92
	Economic and Social	PUE	3.58	0.86
	Car sharing can mitigate traffic problems		3.52	0.99
	Car sharing can reduce greenhouse gas emission and energy consumption.		3.54	1.00
	Car sharing can reduce a number of car parking spaces.		3.69	0.92

Table 52 (continue)

Construct	Item		Mean	SD
Perceived Ease of Use (PEOU)			**3.71**	**0.76**
	I think it is easy to understand how to use car-sharing service.	PEOU1	3.72	0.87
	I think it is easy for me to use car sharing.	PEOU2	3.72	0.86
	I think it is convenient to use car sharing.	PEOU3	3.78	0.86
	The use of car sharing does not require much effort.	PEOU4	3.68	0.88
	I would have no problem if I used car-sharing service.	PEOU5	3.67	0.93
Attitude toward car sharing (ATT)			**3.83**	**0.75**
	I like the concept of car sharing	ATT1	3.92	0.89
	Car sharing is beneficial to society	ATT2	3.83	0.85
	Car sharing is beneficial to the environment	ATT3	3.78	0.92
	Car sharing is beneficial to daily life	ATT4	3.77	0.88
Intention to use car sharing (INT)			**3.68**	**0.80**
	I am interested in car sharing.	INT1	3.72	0.94
	I intend to use car sharing for traveling in the future.	INT2	3.67	0.91
	I plan to use car sharing instead of buying a new car.	INT3	3.55	1.06
	I will inform others of the goodness of this service.	INT4	3.71	0.92
	I support car sharing as a new phenomenon in society.	INT5	3.76	0.90

4.2.3 Preliminary data analysis

Preliminary data analysis required a normality test as it is an assumption of the covariance-based structural equation modeling (SEM). There was no missing data since the web-based survey (Google Form) required to answer the questionnaire completely.

When using large sample procedures as in SEM, it is easy to reject the null hypothesis (consistency with the normal distribution). Thus, it is important to test the normality of the data. Kline (2015) stated that a skewness lower than 3 and kurtosis lower than 7 rules means univariate normality of the data can be assumed. As shown in Table 53, the skewness of the data ranged from -0.886 to 0.097, and the kurtosis ranged from -0.811 to 0.148. It could be concluded that the data were normality distributed, which can process the further analysis of CFA and SEM.

Table 53 The skewness and kurtosis of the data

Variable	skewness	kurtosis
PI1	-0.591	-0.622
PI2	-0.477	-0.352
PI3	-0.886	0.077
EC1	-0.63	-0.349
EC2	-0.515	-0.775
EC3	-0.233	-0.811
EC4	-0.245	-0.606
SI1	-0.395	-0.259
SI2	-0.29	-0.53
SI3	-0.159	-0.515
SI4	-0.191	-0.524
SI5	-0.267	-0.556
PIR	-0.443	-0.015
PFR	-0.21	0.148
PPR	-0.272	-0.115
PUS	-0.035	-0.499
PUC	0.097	-0.774
PUE	-0.189	-0.056
PEOU1	-0.151	-0.213
PEOU2	-0.127	-0.288
PEOU3	-0.077	-0.691
PEOU4	-0.148	-0.203
PEOU5	-0.297	-0.179
ATT1	-0.406	-0.443
ATT2	-0.163	-0.51
ATT3	-0.223	-0.467
ATT4	-0.165	-0.571
INT1	-0.227	-0.435
INT2	-0.154	-0.391
INT3	-0.413	-0.232
INT4	-0.248	-0.21
INT5	-0.188	-0.468

4.2.4 Confirmatory factor analysis (CFA)

The evaluation of the measurement model through a confirmatory factor analysis (CFA) is the first stage of conducting structural equation model (SEM). CFA is used for testing the relationship between the observed variables and the latent constructs. The CFA is commonly used to assess construct validity (Brown, 2006).

4.2.4.1 Measure of fit

Measure of fit was used to compare the theory with reality by comparing the estimate covariance matrix to the observed covariance matrix (Joseph F Hair et al., 2006). There are various types of fit indices and each type has its specific capability in model evaluation. The fit indices used in this study were as follows.

1) CMIN/df (χ^2/df) is the minimum discrepancy divided by its degrees of freedom, which the ratio should be close to 1 for correct model. However, Hair et al. (2006) claimed that the ratio should not exceed 3.

2) GFI is a goodness-of-fit index for ML (Maximum likelihood) and ULS (Unweighted Least Squares) estimation. It calculates the proportion of variance in terms of estimated population covariance (Hooper, 2010).

3) Comparison to a baseline model includes three significant indices: CFI, NFI and TLI. CFI is the comparative fit index, and NFI is the normed fit index, while TLI is the Tucker-Lewis coefficient (Hooper, 2010).

4) RMSEA is the population root mean square error of approximation. It presents how well the model fits a population rather than just the sample. Joseph F Hair et al. (2006) suggested that RMSEA should be between 0.03-0.08.

The results of CFA analysis for a measurement model with AMOS of the original structure is illustrated in Figure 25, and the model fit indicators were shown in Table 54.

Table 54 Fit indicators from CFA of the original model

Indicator	Threshold	Reference	Value	Results
CMIN/df (χ^2/df)	< 3	Hair et al. (2006)	3.290	×
GFI	> 0.9	Hooper (2010)	0.832	×
CFI	> 0.9	Hair et al. (2006)	0.911	✓
NFI	≥ 0.95 good 0.90-0.95 acceptable	Bentler (1990)	0.878	×
TLI	≥ 0.9	Marsh, Hau, and Wen (2004)	0.899	×
RMSEA	0.03-0.08	Hair et al. (2006)	0.067	✓

The results from Table 54 revealed that the model was a poor fit with the values of CMIN/df (χ^2/df), GFI, NFI and TLI do not meet any of the criteria. Moreover, some standardized factor loadings were below 0.5, which Henseler (2017) recommend minimum value of 0.5. Thus, the model was needed to modify.

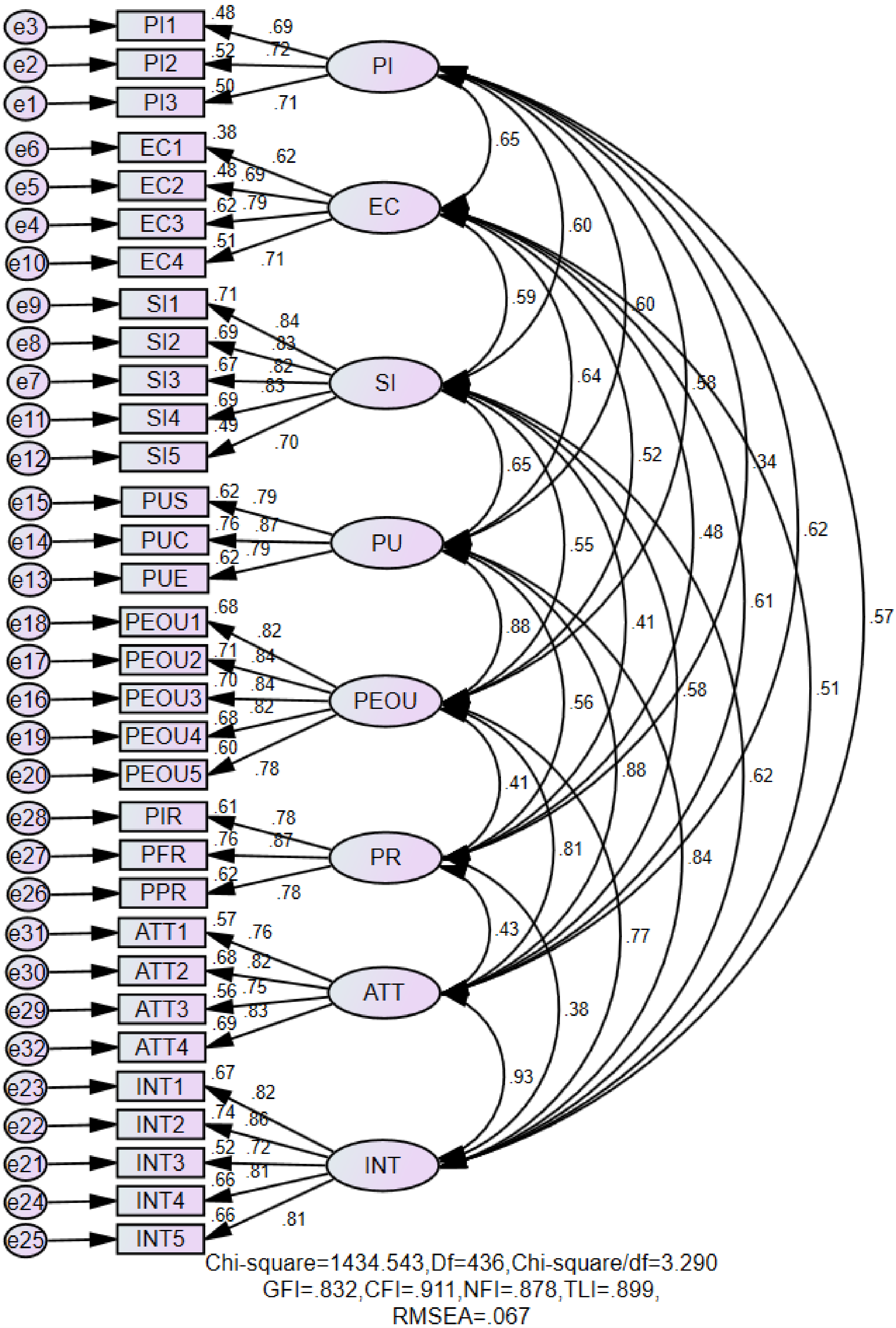


Figure 25 The results of a measurement model of the original structure

In order to modify the model, modification indices (MIs) were used for the suggestion of rearranging observed variables followed guidance from Byrne (1998) and Hair et al. (2011). The model after modified shows in Figure 26 and fit indicators show in Table 55.

Table 55 Fit indicators from CFA of the modified model

Indicator	Threshold	Reference	Value	Results
CMIN/df (χ^2/df)	<3	Hair et al. (2006)	2.519	✓
GFI	>0.9	Hooper (2010)	0.901	✓
CFI	>0.9	Hair et al. (2006)	0.953	✓
NFI	≥ 0.95 good 0.90-0.95 acceptable	Bentler (1990)	0.925	✓
TLI	≥ 0.9	Marsh, Hau & Wen (2004)	0.943	✓
REMSEA	0.03-0.08	Hair et al. (2006)	0.055	✓

After adjusted the model, values of fit indicators, CMIN/df (χ^2/df), GFI, NFI and TLI, were above the threshold. Somehow, eight observed variables were removed. The retained variables illustrate in Table 56.

Table 56 The existed variable after modified the model

Construct	**Item**	**Question**
Personal Innovativeness (PI)	PI1	I usually try a new mobile-based service such as Grab or Lineman.
	PI2	I would not hesitate to try out a new mobile application.
Environmental Concern (EC)	EC3	I consider the potential environmental impact of my actions when making my decisions.
	EC4	I am willing to be inconvenienced in order to take actions that are more environmentally friendly.
Social Influence (SI)	SI1	If my friends or colleagues use car sharing, I will also use car sharing.
	SI2	If a member of my family uses car sharing, I will also use car sharing.
	SI3	If famous people use car sharing, I will also use car sharing.
Perceived Risk (PR)	PIR	Information risk
	PFR	Functional risk
	PPR	Physical risk
Perceived Usefulness (PU)	PUS	Cost Saving
	PUC	Convenience
	PUE	Economic and social

Table 56 (continue)

Construct	Item	Question
Perceived Ease of Use (PEOU)	PEOU1	I think it is easy to understand how to use car-sharing service.
	PEOU2	I think it is easy for me to use car sharing.
	PEOU3	I think it is convenient to use car sharing.
	PEOU4	The use of car sharing does not require much effort.
	PEOU5	I would have no problem if I used car- sharing service.
Attitude toward car sharing (ATT)	ATT1	I like the concept of car sharing
	ATT2	Car sharing is beneficial to society
	ATT4	Car sharing is beneficial to daily life
Intention to use car sharing (INT)	INT2	I intend to use car sharing for traveling in the future.
	INT3	I plan to use car sharing instead of buying a new car.
	INT4	I will inform others of the goodness of this service.
	INT5	I support car sharing as a new phenomenon in society.

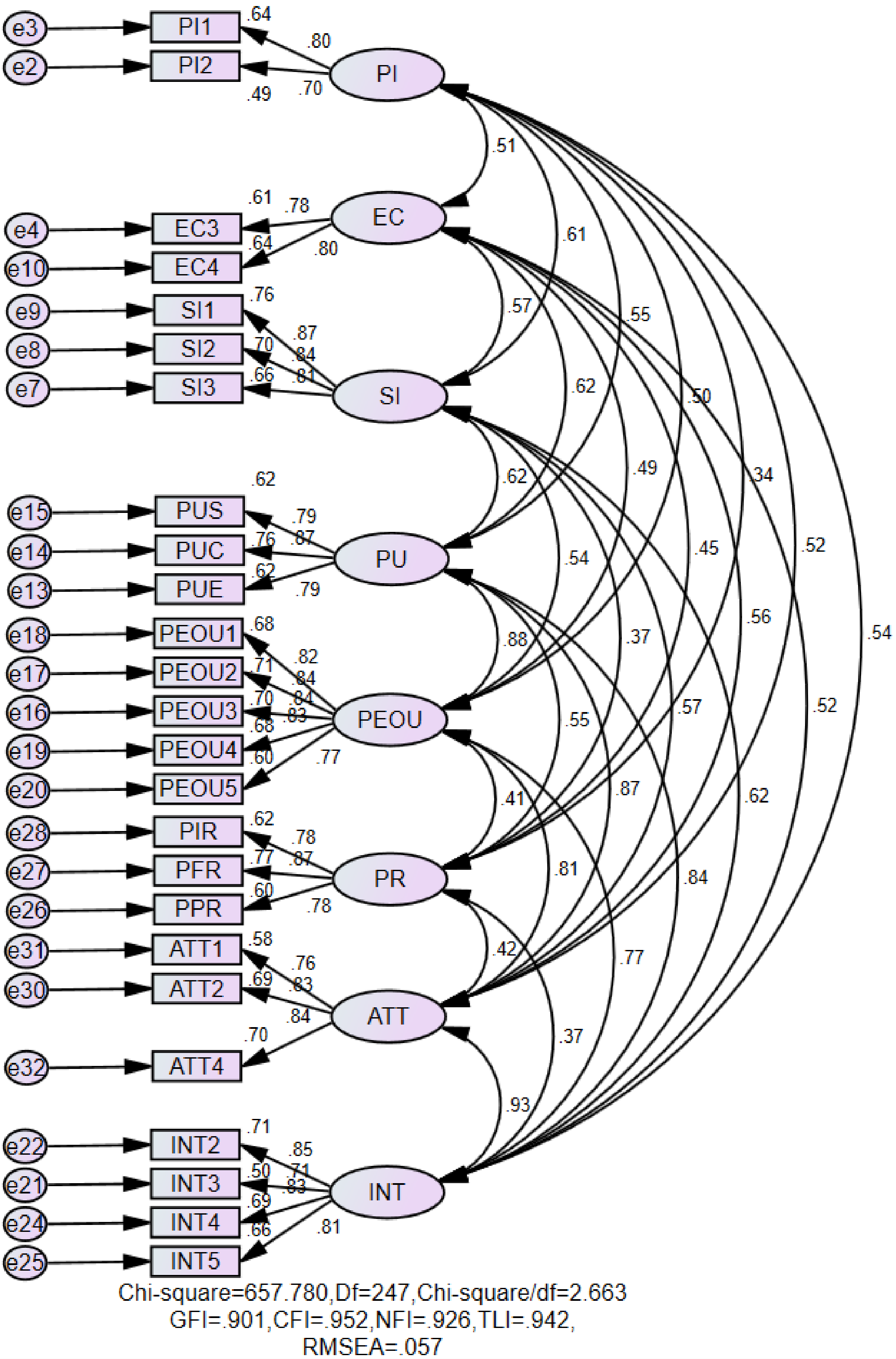


Figure 26 The results of a measurement model of the modified structure

4.2.4.2 Assessment of measurement model

1) Indicator reliability

Outer loadings or factor loadings were measured for indicator reliability (Joe F Hair et al., 2011). The value of outer loading were between 0 and 1, high outer loadings mean that the indicators of a construct have a large degree of similarity (Hair et al., 2017). Therefore, the value of outer loading closer to 1 indicates more reliability (Garson, 2016).

2) Construct reliability

Reliability refers to the indicators' internal consistency and their ability to generate the same findings under the same situations (Field, 2013). Reliability assessment of the measurement model is important because the structural model evaluation results may be biased if it lacks reliability (Joe F Hair, Sarstedt, Ringle, & Mena, 2012). Generally, Cronbach's alpha (CA) was used in social science studies for measuring the reliability. However, some studies also reported composite reliability (CR) because Cronbach's alpha tends to underrate the reliability values, while composite reliability tends to overrate the reliability values (J. Hair et al., 2017). Therefore, J. Hair et al. (2017) suggested that researchers should report Cronbach's Alpha and composite reliability.

(1) Composite reliability was used to measure the internal consistency that represents how a construct is explained by its assigned items. The formula for composite reliability (Alarcón, Sánchez, & De Olavide, 2015) was

$$\mathrm{CR}_j = \frac{\left(\sum_{k=1}^{Kj} \lambda_{jk}\right)^2}{\left(\sum_{k=1}^{Kj} \lambda_{jk}\right)^2 + \theta_{jk}}$$

Where:

K_j = number of items of the construct *j*

λ_{jk} = the factor loadings of item k from the construct *j*

θ_{jk} = error variance of the kth item from the construct *j*

(2) Cronbach's alpha (Cr α) is a measure of consistency that reflects how closely related is a set of items as a group. The Cronbach's alpha can be calculated (Fink & Litwin, 1995) from

$$\mathrm{Cr}\,\alpha = \frac{\mathrm{K} \times \sigma}{\tau + (\mathrm{K} - 1) \times \sigma}$$

Where:

K = the number of items measuring the construct

σ = average covariance between pairs of items

τ = the variance of the sum of all indicators scores

3) Convergent validity

Convergent validity refers to the extent to which an indicator is positively correlated with other indicators in the same construct (Sekaran & Bougie, 2016). Convergent validity is achieved when the outer loading of each indicator is above 0.7

and average variance extracted (AVE) of each construct is 0.5 or above (J. Hair et al., 2017). The formula for AVE (Alarcón et al., 2015) is illustrated below:

$$\text{AVEj} = \frac{\sum_{k=1}^{Kj} \lambda_{jk}^{2}}{\sum_{k=1}^{Kj} \lambda_{jk}^{2} + \theta_{jk}}$$

Where:

K_j = number of items of the construct *j*
λ_{jk} = the factor loadings of item k from the construct *j*
θ_{jk} = error variance of the kth item from the construct *j*

Table 57 Criteria for the measurement model assessment

Test		Criteria	References
Indicator reliability	Factor Loading	>0.7 ≥ 0.5 acceptable	Chin (1998); Henseler, Ringle, and Sinkovics (2009)
Construct Reliability	Composite Reliability (CR)	> 0.7	Hair et al. (2006)
	Cronbach's Alpha (CA)	> 0.6	Hair et al. (2006)
Convergent Validity	Average Variance Extracted (AVE)	> 0.5	Fornell and Larcker (1981)

The results of measurement model assessment in Table 58 revealed that the factor loadings, Cronbach alpha, the composite reliability (CR) and the average variance extracted (AVE) were all above the recommended criteria (references in Table 58). The indicator reliability was measured by factor loading. The results found that most of factor loading values were considered as good (0.706-0.875), only PI2 was 0.699, which was acceptable (Chin, 1998; Henseler et al., 2009). Cronbach alpha values were between 0.710-0.911 indicating that all internal consistency reliabilities were good. The Composite Reliability (CR) of PI and EC were 0.710 and 0.777, which above 0.7 indicating acceptable reliability (Sekaran & Bougie, 2016). However, CR values of the other constructs were above 0.8, which were considered as good reliability (Sekaran & Bougie, 2016). The average variance extracted (AVE) values exceeded 0.5 demonstrating the convergent reliability of the constructs.

Table 58 Measurement model results

Construct	Item	Factor loading	t-value	Cronbach Alpha	CR	AVE
Criteria		> 0.7		> 0.7	> 0.7	> 0.5
PI	PI1	0.800	Ø	0.710	0.721	0.564
	PI2	0.699	11.412			
EC	EC3	0.783	Ø	0.770	0.772	0.628
	EC4	0.802	13.776			

Table 58 (continue)

Construct	Item	Factor loading	t-value	Cronbach Alpha	CR	AVE
Criteria		> 0.7		> 0.7	> 0.7	> 0.5
SI	SI1	0.872	Ø	0.878	0.879	0.708
	SI2	0.838	22.549			
	SI3	0.814	21.729			
PR	PIR	0.785	Ø	0.846	0.854	0.662
	PFR	0.875	18.998			
	PPR	0.777	17.604			
PU	PUS	0.790	Ø	0.857	0.858	0.670
	PUC	0.873	22.078			
	PUE	0.789	19.380			
PEOU	PEOU1	0.823	Ø	0.911	0.912	0.674
	PEOU2	0.843	22.612			
	PEOU3	0.838	22.425			
	PEOU4	0.825	21.898			
	PEOU5	0.773	19.944			
ATT	ATT1	0.761	Ø	0.849	0.850	0.654
	ATT2	0.828	19.437			
	ATT4	0.835	19.625			
INT	INT2	0.845	Ø	0.872	0.876	0.640
	INT3	0.706	17.955			
	INT4	0.830	22.831			
	INT5	0.812	22.062			

Ø is the value was fixed at 1 for model identification purposes.

4.2.5 Structural equation model (SEM)

4.2.5.1 Measure of fit

After an acceptable measurement model was found, a structural model based on the modified CFA measurement model was created. The structural model comprised eight latent variables with 25 observed variables (Table 56). Rather than explain relationships in a single equation as with regression analysis, SEM can test a set of relationships with multiple equations. Thus, SEM requires specific measure of fit or predictive accuracy that reflect the overall model rather than specific relationship.

The overall goodness of fit of model assessment was conducted using seven model-fit measures from three categories: Absolute fit indices, Incremental fit indices and Parsimonious fit. This study reported Chi-Square, Relative Chi-Square (CMIN/df), goodness of fit index (GFI), comparative fit index (CFI), normed fit index (NFI), Tucker-Lewis Index (TLI), and Root Mean-Square Error of Approximation (RMSEA).

The results of model fit of the original structural model revealed that the fit indices were not at an acceptable level (CMIN/df = 4.202, GFI = 0.840, CFI = 0.900, NFI = 0.873, TLI = 0.866 RMSEA = 0.080) as shown in Table 59. So, the model needs to be modified. O'Rourke and Hatcher (2013) suggested that the researcher should consider modification indices in order to determine how to modify the model. In this study, the modification indices recommended to add the relationship between three exogenous latent constructs: Personal Innovativeness (PI), Environmental Concern (EC) and Social Influence (SI).

Table 59 Model fit results for original structural model

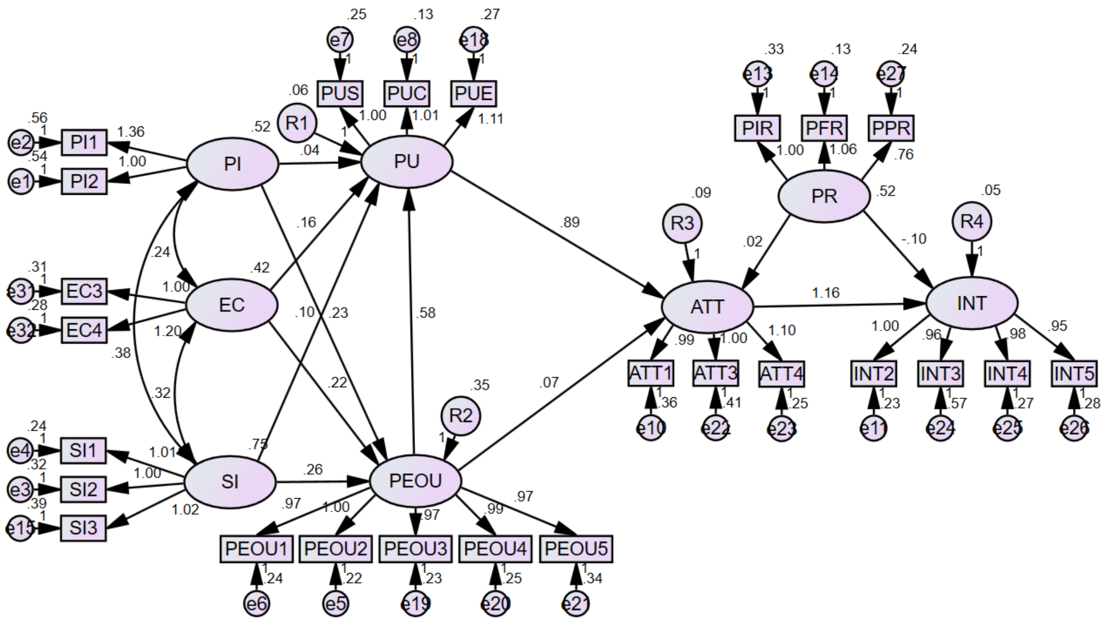
Indicator	Threshold	Reference	Value	Results
CMIN/df (χ^2/df)	<3	Hair et al. (2006)	4.202	×
GFI	>0.9	Hooper (2010)	0.840	×
CFI	>0.9	Hair et al. (2006)	0.900	✓
NFI	≥ 0.95 good 0.90-0.95 acceptable	Bentler (1990)	0.873	×
TLI	≥ 0.9	Marsh, Hau & Wen (2004)	0.886	×
RMSEA	0.03-0.08	Hair et al. (2006)	0.080	✓

After the theorical model was modified, the revised model was tested again. The final model had adequate model fit with CMIN/df of 2.650, which was below the recommended maximum value of three. The GFI and CFI values of 0.902 and 0.947, exceeded the minimum criterion of 0.9. The NFI value of 0.918, which was acceptable value. The TLI value of 0.937 was close to 1 and indicated good model fit. The RMSEA of 0.057 indicated reasonable errors of approximation in the population (Byrne, 2010). The results of model fit for structural model are shown in Table 60.

An unstandardized and a standardized model are presented in Figure 27 and Figure 28, respectively. In the unstandardized structural model, the regression weights, covariances, intercepts and variances were showed in the path diagram. Meanwhile, the standardized regression weight, correlation, squared multiple correlations were demonstrated in the standardized model. The standardized regression weights and the correlations are independent of the units in which all variables are measured and will not be affected by the choice of identification constraints (Arbuckle, 2005).

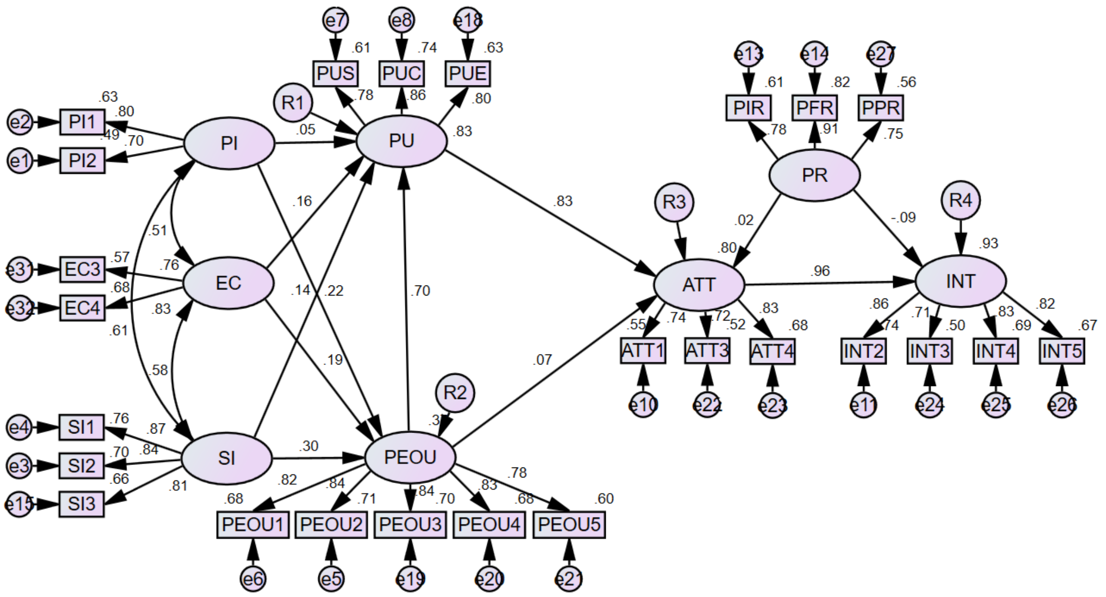
Table 60 Model fit results for modified structural model

Indicator	Threshold	Reference	Value	Results
CMIN/df (χ^2/df)	<3	Hair et al. (2006)	2.650	✓
GFI	>0.9	Hooper (2010)	0.902	✓
CFI	>0.9	Hair et al. (2006)	0.947	✓
NFI	≥ 0.95 good 0.90-0.95 acceptable	Bentler (1990)	0.918	✓
TLI	≥ 0.9	Marsh, Hau & Wen (2004)	0.937	✓
RMSEA	0.03-0.08	Hair et al. (2006)	0.057	✓



Chi-square=711.821,Df=255,Chi-square/df=2.791
GFI=.902,CFI=.946,NFI=.918,TLI=.936,
RMSEA=.060

Figure 27 An unstandardized model



Chi-square=711.821,Df=255,Chi-square/df=2.791
GFI=.902,CFI=.946,NFI=.918,TLI=.936,
RMSEA=.060

Figure 28 A standardized model

4.2.5.2 Squared multiple correlations (SMC)

The assessment of model fit provide information about how well the model fits the empirical data, but the strength of the structural paths in the model is determined by squared multiple correlations (SMC). SMC is the proportion of its variance that is accounted by its predictors. Thus, it is important to consider the SMC of each dependent variable together with fit measures for the best describing the structural model (Arbuckle, 2005). To interpret the R^2 statistic in multiple regression analysis is similar to SMC (Sharma, 1996).

The squared multiple correlations of the modified model are shown in Table 61. The results of SMC revealed that the structural model explained 36.9% of the variance in perceived ease of use, 83.5% of the variance in usefulness, 80.4% of the variance in attitude toward car sharing and 92.8% of the variance in customers' intention to use car sharing.

Table 61 Square multiple correlations

	R^2
PU	0.835
PEOU	0.369
ATT	0.804
INT	0.928

Weak effect: $R^2 = 0.19$
Moderate effect: $R^2 = 0.33$
High effect: $R^2 = 0.67$ (Chin, 1998)

4.2.5.3 Hypothesis testing

The research hypotheses of this study had been statistically supported by the test performed in the previous section, model fit and global test of variance explained (R^2). In this part, the hypotheses of relationships between variables will be assessed. The estimate regression weight of the final model is illustrated in Table 62.

Table 62 The estimate regression weight of the final model.

			Estimate	S.E.	C.R.	P	Label
PEOU	<---	PI	0.230	0.069	3.320	***	par_18
PEOU	<---	SI	0.256	0.056	4.572	***	par_19
PEOU	<---	EC	0.221	0.071	3.129	0.002	par_26
PU	<---	PI	0.040	0.039	1.038	0.299	par_17
PU	<---	SI	0.100	0.032	3.169	0.002	par_20
PU	<---	EC	0.156	0.041	3.845	***	par_25
PU	<---	PEOU	0.584	0.040	14.631	***	par_27
ATT	<---	PU	0.887	0.104	8.545	***	par_21
ATT	<---	PEOU	0.066	0.075	0.889	0.374	par_22
ATT	<---	PR	0.023	0.030	0.763	0.445	par_36
INT	<---	ATT	1.159	0.065	17.950	***	par_23
INT	<---	PR	-0.101	0.034	-2.997	0.003	par_28
PI2	<---	PI	1.000				
PI1	<---	PI	1.358	0.119	11.367	***	par_1
SI2	<---	SI	1.000				
SI1	<---	SI	1.013	0.045	22.497	***	par_2
PEOU2	<---	PEOU	1.000				
PEOU1	<---	PEOU	0.971	0.042	22.867	***	par_3
PUS	<---	PU	1.000				
PUC	<---	PU	1.005	0.047	21.325	***	par_4
ATT1	<---	ATT	0.994	0.062	16.153	***	par_5
INT2	<---	INT	1.000				
PIR	<---	PR	1.000				
PFR	<---	PR	1.059	0.057	18.611	***	par_6
SI3	<---	SI	1.015	0.049	20.864	***	par_7
PUE	<---	PU	1.111	0.058	19.276	***	par_8
PEOU3	<---	PEOU	0.972	0.042	23.145	***	par_9
PEOU4	<---	PEOU	0.989	0.043	22.754	***	par_10
PEOU5	<---	PEOU	0.974	0.047	20.688	***	par_11
ATT3	<---	ATT	1.000				
ATT4	<---	ATT	1.100	0.061	18.047	***	par_12
INT3	<---	INT	0.956	0.051	18.662	***	par_13
INT4	<---	INT	0.984	0.042	23.477	***	par_14
INT5	<---	INT	0.946	0.041	22.877	***	par_15
PPR	<---	PR	0.761	0.044	17.228	***	par_16
EC3	<---	EC	1.000				
EC4	<---	EC	1.201	0.092	13.027	***	par_24

Hypothesis testing results

From thirteen hypotheses of this study, nine hypotheses were supported (Table 63 and Figure 29). The hypotheses from the original technology acceptance model (TAM) found a significant relationship (H_1, H_3, H_4), while H_2 had no significant effect. It can be interpreted that perceived usefulness has a significant effect on attitude toward car sharing (ATT), while perceived ease of use (PEOU) had no significant effect on ATT but significantly affected PU. Also, ATT significantly affected intention to use car sharing (INT).

For the exogenous latent construct, firstly, Personal innovativeness (PI), had no significant effect to Perceived usefulness (PU), so hypothesis H_5 was rejected. However, PI had a significant effect on PEOU (Perceived ease of use). The second external construct, Environmental concern (EC), was found to be a significant determinant of PU and PEOU. Thus, both of the proposed hypotheses regarding EC's effect on PU and PEOU (H_7 and H_8) were supported. As expected, social influence had significant effects on PU and PEOU. So, hypothesis H_9 and H_{10} were supported. Lastly, perceived risks (PR) were not found the significant effect to ATT, but PR had the negative effect to INT. Hence, H_{11} was rejected, while H_{12} was supported.

Moreover, the influences of each exogenous variables on the endogenous variables were measured by testing the standardized total effects, direct and indirect effects associated with each variable.

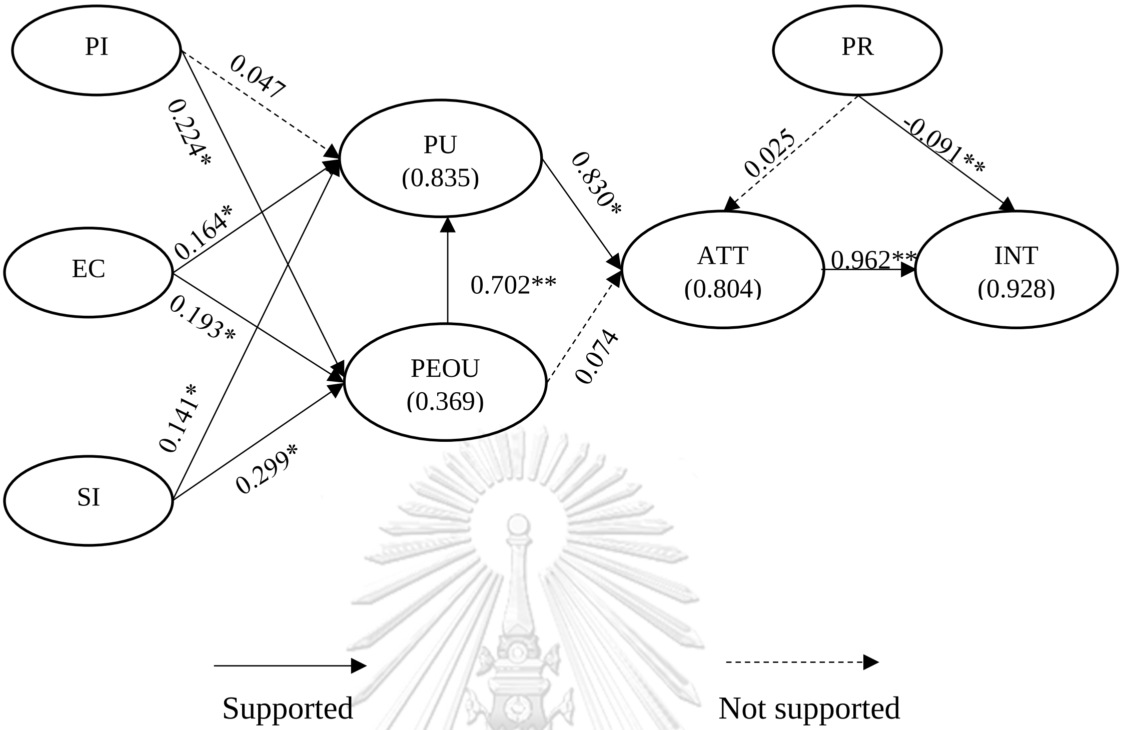
The regression weight of each path was also tested. The regression weights represent the determinant's direct on the respective endogenous variable. For instance, the regression weight of direct effect of PU on ATT is 0.830. That means, one standard deviation increase in PU would increase ATT by 0.830 standard deviations.

The regression weights were found ranging from -0.091 to 0.962. All four exogenous variables (PI, EC, SI and PR) were found to be statistically significant determinants of the four endogenous variables (PU, PEOU, ATT and INT). The endogenous variable PU was found to be significantly determined by three variables PEOU (β = 0.702, $p < 0.001$), EC (β = 0.164, $p < 0.001$) and SI (β = 0.141, $p < 0.05$). The R^2 of PU is 0.835, indicating that 83.5% of the variance of PU is explained by PEOU, EC and SI. PEOU was found to be significantly determined by PI (β = 0.224, $p < 0.001$), EC (β = 0.193, $p < 0.05$) and SI (β = 0.299, $p < 0.001$), resulting in the R^2 of 0.369. That means 36.9% of variance of PEOU is explained by PI, EC and SI. For ATT, the significant determinants were PU (β = 0.830, $p < 0.001$) with R^2 of 0.804. So, 80.4% of the variance of ATT is explained by PU. Finally, INT was found to be significantly determined by ATT (β = 0.962, $p < 0.001$) and PR (β = -0.091, $p < 0.05$) with R^2 of 0.928, indicating that 92.8% of the variance of INT is explained by ATT and PR.

Table 63 Hypothesis testing results

Hypothesis		Path	P	Support	Regression weight
H_1	Perceived usefulness positively affects Attitude	PU→ATT	***	Yes	0.830
H_2	Perceived ease of use positively affects Attitude	PEOU→ATT	0.374	No	0.074
H_3	Perceived ease of use positively affects Perceived usefulness	PEOU→PU	***	Yes	0.702
H_4	Attitude positively affects Intention to use	ATT→INT	***	Yes	0.962
H_5	Personal innovativeness positively affects the perceived usefulness	PI→PU	0.299	No	0.047
H_6	Personal innovativeness positively affects the perceived ease of use	PI→PEOU	***	Yes	0.224
H_7	Environmental concern positively affects the perceived usefulness	EC→PU	***	Yes	0.164
H_8	Environmental concern positively affects the perceived ease of use	EC→PEOU	0.002**	Yes	0.193
H_9	Social influence positively affects perceived usefulness	SI→PU	0.002**	Yes	0.141
H_{10}	Social influence positively affects perceived ease of use	SI→PEOU	***	Yes	0.299
H_{11}	Perceived risk negatively affect attitude toward car sharing	PR→ATT	0.445	No	0.025
H_{12}	Perceived risks negatively affect customers' intention to use car sharing	PR→INT	0.003**	Yes	-0.091

*** $p < 0.001$, **$p < 0.01$



*** $p < 0.001$, ** $p < 0.01$

Figure 29 The results of hypothesis testing

Effects of external variables on Intention to use car sharing

When calculate the effects of external variables on intention to use car sharing, the results showed that social influence (SI) had the highest weight on intention to use car sharing (INT), followed by Environmental concern (EC), personal innovativeness (PI), and perceived risk, respectively.

Table 64 Effects of External Variables on intention to use car sharing

Variable	**Total effects**
Personal Innovativeness (PI)	0.125
Environmental concern (EC)	0.230
Social influence (SI)	0.294
Perceived risk (PR)	-0.091

Chapter 5
Conclusion and Discussion

The objectives of this research were 1) to explore factors influencing the probability of using car-sharing services and 2) to investigate customers' attitudes toward intention to use car-sharing services. Thus, this research was divided into two phases of study to meet the research objectives. A quantitative research method was applied to both studies. The results of these two studies were reported in the previous chapter.

This chapter summarized key findings of the two studies. Next, the results of these studies were discussed in comparison to the theory, previous studies and conceptual framework of this research. This section followed by implications and limitations of this research. The final section will give suggestions for future studies. This chapter will present in order as follows:

5.1 Key findings of Study One
- 5.1.1 Demographic characteristics
- 5.1.2 Travel behaviors
- 5.1.3 Customers' preference of car-sharing service
- 5.1.4 Factors influencing the probability of using car sharing

5.2 Key findings of Study Two
- 5.2.1 Demographic characteristics
- 5.2.2 The extended technology acceptance model

5.3 Discussion
5.4 Research implication
5.5 Research limitation
5.6 Suggestion for future research

5.1 Key findings of Study One

From a quantitative methodology approach, the questionnaire survey was conducted through survey with an online-questionnaire. Multi-stage sampling methods were applied to the target group which was selected by age older than 18 years old living, studying, or working in Bangkok. There were 204 respondents were participated in this survey. However, there are three scenarios for each respondent. Thus, there are 612 observations in total. The data obtained from this study were analyzed using descriptive statistics (percentage, mean, standard deviation) and multiple linear regression analysis under the concept of logistic regression. The key findings from this study can be summarized as follows.

5.1.1 Demographic characteristics

An analysis of the sample revealed there were twice as many female respondents as male. The majority of the respondents were aged between 20-40, which was expected to be the main target group for car-sharing services. The main occupation group was full-time worker. Most of the respondents had a personal monthly income of less than 20,000 Baht. The main group of respondents was living with other three people per household (a total four people in a household). Most of the respondents possessed one car, and held a driving license.

5.1.2 Travel behaviors

The largest group of respondents was made up of those who usually drove their own car. The second largest group generally used public transport, while the third largest group was constituted by those who normally traveled in a private car as a passenger. Most respondents traveled five days a week and the majority of them traveled alone. Purpose of travel was mainly work or study. The average travel distance was 27.11 kilometers with the average travel duration 74.15 minutes. The average walking distance from home to car park or bus stop was 183.50 meters, and the return from office or university to car park or bus stop was 212.09 meters. The average daily expense was 139.92 Baht.

Most respondents had some experience of using a ride-hailing service. For the people who had ever used a ride hailing service, most of them used it less than once a month, for work or study. The average total cost for the service was 111.65 Baht.

5.1.3 Customers' preference of car-sharing services

The results revealed that most respondents were unaware of car-sharing services, and only few of them have used car-sharing services. In terms of the intended use of car-sharing services, most respondents used them for work or study purposes, with the next largest group choosing car sharing for purposes of travel and relaxation, followed by shopping. More than one third of the participants tend to use car sharing to replace the current mode of travel, while another one third was likely to use car sharing to connect other modes. The average longest distance they were able to walk to a car-sharing station was 458.98 meters, and the average longest waiting time for car availability was 19.52 minutes. The majority of the respondents indicated that they 50% probably use car sharing. It means that most people were hesitate to use this new service.

5.1.4 Mean different test

Mean different test in the Study One aimed to compared the probability of using car sharing in the group of dependent variables dependently. The results revealed that the mean difference was found with ten variables: age, employment status, mode of travel, travel purpose, ride-hailing experience, ride-hailing monthly frequency, purpose of using ride-hailing, car-sharing experience, expected activity of using car sharing and expected reason of using car sharing.

5.1.5 Regression analysis

This study categorized the factors influencing the probability of using car sharing into three main types: socio-demographic, travel behaviors and car-sharing preferences.

(1) The results indicated the socio-economic status of the respondents did not affect the probability of using car-sharing.

(2) In terms of travel behavior, travel mode, travel purpose, walking distance and experience of using ride-hailing service affected the probability of using car sharing. The people who drive their own private car were more likely to use car sharing than both a) people who were private car passengers and b) people who used both private car and public transport. People who travel for work or study had more probability to use car sharing than other groups. In terms of walking distance, the longer walking distance, the greater likelihood of using car sharing. Lastly, the probability of using car sharing increased when people had experience of using ride-hailing services.

(3) The last group of factors is car-sharing preference. The significant factors influencing the probability of using car sharing comprise experience of using car sharing, expected activity to use car sharing, a reason for using car sharing, acceptable longest waiting time for shared car available and the price of the service. First of all, a car-sharing experience had a positive significant influence the intention to use car sharing. Secondly, people who intend to use car sharing for work or study were more likely to use car sharing than people who intend to use car sharing for travel or relax. Next, people were more likely to use car sharing to replace their current mode of travel than connect to other modes of travel. Moreover, the acceptable longest waiting time for shared car availability was significant in relation to customers' intention to use car sharing. For more details, people who can wait patiently were more likely to choose car sharing. As might be expected, the probability of using car sharing decreased when the price of using the service increased.

5.2 Key findings of Study Two

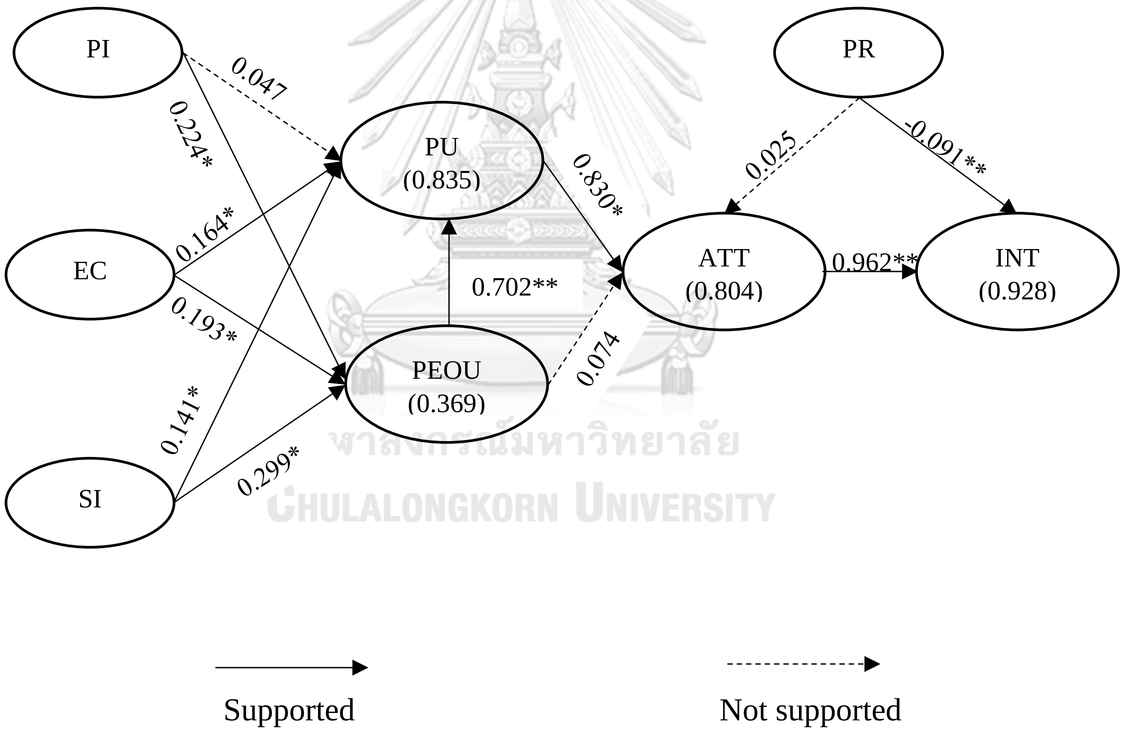
Study Two aimed to investigate the latent attitude influencing the users' intention to use car sharing. Technology Acceptance Model (TAM) framework was applied as the basic theorical framework. Nevertheless, four antecedent variables: Personal innovativeness (PI), Environmental concern (EC), Social influence (SI) and Perceived risk (PR) were included in the TAM model. The questionnaire survey was conducted with the target population aged 18 and older, living, studying or working in Bangkok. In total, 505 participants completed the questionnaire. The data obtained from this study were analyzed using the structural equation model (SEM). The key findings were presented as follows.

5.2.1 Demographic characteristics

The characteristics of respondents in Study Two show that the proportion of males was one third that of females. The majority of the respondents were in the age range 20-40, which was considered as the target group for car-sharing services. The main employment status was full-time staff. Personal monthly income was mainly in a less than 20,000 Baht group. Most respondents owned one car. The majority of the respondents commute by driving their own private car. The main group of respondents had never experienced car-sharing services.

5.2.2 The extended technology acceptance model

The validity of TAM in determining users' attitudes toward car-sharing services was examined in this study. Moreover, the direct relationship between external variables of personal innovativeness (PI), environmental concern (EC), social influencing (SI) and perceived risk (PR) and the dependent variables of perceived usefulness (PU), perceived ease of use (PEOU), attitude toward car sharing (ATT), and intention to use car sharing (INT) were examined. Before running SEM, confirmatory factor analysis (CFA) was conducted in order to test the internal consistency and structural reliability of measurement items in determining customers' intention to use car sharing service. The results of SEM showed that the structural model was fit with the empirical data. The results of the proposed hypotheses testing are illustrated in Figure 29.



*** p < 0.001, ** p < 0.01

Figure 30 Results of hypotheses testing

The results of hypotheses testing revealed that nine out of 12 path relationships in the structural model were supported. The TAM framework was validated in this study. However, not all of the hypotheses on TAM on customers' acceptance of car-sharing services in Bangkok were supported. In greater detail, perceived usefulness (PU) had a direct effect on attitude toward car sharing (ATT). On the other hand, the results of perceived ease of use (PEOU) conflict with the proposed theoretical framework. PEOU was found to have no significant effect on ATT, but it had a positive effect on PU. As expected, ATT was found to be a significant determinant of intention to use car sharing (INT). Therefore, H_1, H_3 and H_4 were accepted, while H_2 was rejected.

The first external variable was personal innovativeness (PI), which is important for individual acceptance of a new technology. Thus, it was hypothesized that PI had a direct positive effect on PU and PEOU. However, the results indicated that PI only had a significant effect on PEOU. Thus, H_6 was accepted, while H_5 was rejected. The results suggested that people with innovative characters think that car-sharing systems are easy to use but they do not perceive them to be useful.

The previous studies confirmed that car sharing benefits to the environment by lowering the fuel consuming and greenhouse gases emission. Thus, environmental concern was considered to be one of the antecedent variables. The results from hypotheses testing revealed that environmental concern (EC) had a positive direct effect on both PU and PEOU. Hence, H_7 and H_8 were accepted.

Social influence (SI) was an important factor for those who may hesitate to adopt a new technology. They may need the information or opinion from people they trust. So, social influence was selected to be an antecedent variable. The results confirmed that SI had a positive significant effect on PU and PEOU. So, H_9 and H_{10} were accepted.

Car sharing systems involve new technology, so people may be concerned about electronic risks, as well as physical risks associated with a vehicle. This perceived risk (PR) was a resistance to adopt new technology. Thus, H11 and H12 were developed as PR had a negative effect on ATT and INT, respectively. The results indicated that PR only had a negative effect on INT but did not have any effect on ATT. Therefore, H_{11} was rejected but H_{12} was accepted.

5.3 Discussion

5.3.1 Factors influencing the probability of using car sharing

Two techniques were employed for examining the significant factors influencing the probability of using car sharing: Mean different test and Multiple linear regression. The variables were categorized into three groups: socio-economic, travel characteristics and car-sharing preference attributes. For socio-economic factors, age was found the significant differences in mean comparison, while multiple linear regression did not find an effect on the probability of using car-sharing. The result found that people who are between 21-40 years old are more likely to use car-sharing than people who are 41-60 years old. As expected, the target group of car sharing was young adults. The finding was also consistent with prior studies of Fukuda et al. (2005); Le Vine et al. (2014); De Luca et al. (2015); Carteni et al. (2016); Wang and Yan (2016).

The remaining significant factors discovered in mean different tests were also discovered to be significant factors when analyzing with multiple linear regression analysis. Multiple linear regression analysis revealed that the significant factors towards the intention to use car-sharing included mode of transport, travel purpose, walking distance, ride-hailing experience, car-sharing experience, the expected purpose of using car-sharing, expected reason for using car-sharing and the price of the service. In greater details, the people who drive were more likely to choose car-sharing than other modes of travel. This was not in accordance with the previous studies of Efthymiou et al. (2013), De Luca & Di Pace (2014), Efthymiou & Antoniou (2016), and Wang & Yan (2016) that car-sharing is attractive to people who travel mainly by public transport. The reason may be because the drivers have been facing traffic problems, such as traffic jams and insufficient car parks, which caused stress on the road. Besides, they also pay the cost of vehicle ownership. Therefore, they may want to eliminate these problems by using car sharing.

The results showed that the people who traveled for work or study tended to be more willing to use car sharing than the people who traveled in order to go shopping. This is inconsistent with the study of Cartenì et al. (2016), which found that the users traveling for work purposes were less willing to switch to car sharing. Moreover, Efthymiou et al. (2013) found that people who use taxis for their social activity tended to use car sharing. This may be because the majority of the respondents in this study were full-time staff, so they mainly traveled for work.

The results found that walking distance from home/office/university to parking area/bus stop had a significant influence on the use of car sharing. Whether the walking distance from home, office or university to car-park or bus stop, the longer the distance a person had to walk, greater the likelihood of car-sharing. As expected, people tend to use a motorize vehicle if they have to walk a long distance.

The experience of using mobile-app taxis or ride-hailing services also influenced the customers' intention to use car sharing. People familiar with mobile-app taxi services tended to be more willing to use car-sharing. Similarly, people who had experience of using car sharing were more likely to use car sharing. People who are open-minded to new technology were more disposed to try new things.

In general, the respondents tended to use car sharing for work or study rather than travel or relaxation. Also, people tended to use car sharing to replace their usual mode of transport. The findings were different from the previous study of (D. Kim et al., 2015), which found people were likely to use car sharing for leisure or personal purposes.

The waiting time for shared-car availability also influenced the intention to use car-sharing. People who had more patience to wait tended to be more likely to use car sharing. The average longest waiting time was about 19.52 minutes, which was consistent with the study of Fukuda et al. (2005) that found people willing to wait approximately 15-20 minutes for a shared car.

As expected, the price of the service affected the probability of using car-sharing. It confirmed the previous literature that when the cost of car sharing increased, the probability of car sharing decreased (Fukuda et al., 2005; Chevalier & Lantz, 2015; (J. Kim, S. Rasouli, & H. Timmermans, 2017; J. Kim, S. Rasouli, et al., 2017b).

5.3.2 An extended technology acceptance model

In this research, the technology acceptance model (TAM) was validated in the context of car-sharing service acceptance in Bangkok. Based on the proposed model, four external variables were added on the four original TAM constructs. These were personal innovativeness (PI), environmental concern (EC), social influence (SI) and perceived risk (PR).

In this study, perceived usefulness (PU) referred to which customers in Bangkok believed that car sharing is useful for their commute in terms of cost saving, convenience, and environmental and social benefits. The result of hypothesis "PU has a positive direct effect to attitude towards car sharing (ATT)" was accepted and showed that PU has a strong relationship with ATT. The result was consistent with the TAM framework of Davis (1986) and previous studies of car-sharing adoption (Lee et al., 2003; Barnes & Mattsson, 2017; Kim et al., 2017; Liu & Yang, 2018; Müller, 2019; Schlüter & Weyer, 2019) that indicated the usefulness of the target technology is a critical determinant of user behavioral decisions (Lu, 2014). It can be inferred that if customers realize the benefits of car sharing, they tend to use the service.

On the other hand, perceived ease of use (PEOU) referred to which customers think that car-sharing systems are easy to use or do not require significant effort. This study proposed the hypothesis that PEOU has a positive direct effect on ATT. The result indicated that PEOU does not have a significant effect on ATT. It means that PEOU was not the determinant of ATT. This result was inconsistent with the study of Lee et al. (2003); Liu & Yang (2018); Cheng et al. (2019); Müller (2019); Schlüter & Weyer (2019) that found a positive relationship between PEOU and ATT. However, the result was in accordance with Jayasingh & Eze (2010) that found PEOU is not a critical determinant factor of user behavioral decisions as the PU. It is because PEOU has a direct impact on the post-adoption stage rather than the pre-adoption stage. However, another hypothesis about PEOU, that PEOU directly influences PU, was accepted. This result was consistent with the TAM framework (Davis, 1986) and the study of Müller (2019) and (E. S.-T. Wang & Chou, 2014). When people perceive ease of use of the technology, usefulness is also likely to be perceived, which in turn leads them to form positive attitudes toward the technology (H. Kim et al., 2017). Therefore, people with a positive attitude towards a car-sharing system are positively associated with the intention to use the service (Claasen, 2020).

As expected, the results of this research revealed that ATT directly influence INT. It was consistent with the TAM framework (Davis, 1986) and prior studies of car-sharing service (H. Kim et al., 2017; Müller, 2019), bike-sharing service (P. Cheng et al., 2019) and shared mode (Claasen, 2020), park and ride service (Ibrahim et al., 2020). It can imply that when people have positive attitude toward the new technology, they tend to use that technology.

Personal Innovativeness

Personal innovativeness refers to the degree to which an individual is likely to adopt new technologies. Unlike the previous studies (Y. Wang et al., 2020), the results did not find the effect of personal innovativeness on perceived usefulness. However, personal innovativeness had a direct effect on perceived ease of use. Obviously, the people with high level of innovativeness will have high ability to use the new technology. Somehow, perceived ease of use had a direct effect on perceived usefulness. This means that personal innovativeness had an indirect effect on perceived usefulness, and that perceived usefulness had a direct effect to attitude.

Lastly, attitude directly affected to intention to use car sharing. It can be concluded that personal innovativeness positively influences the intention of customer to use car-sharing services through the perceived usefulness and perceived ease of use. The results were consistent with the prior studies of H. Kim et al. (2017); Müller (2019); Schlüter & Weyer (2019) and Wang et al. (2020).

Environmental concern

In this research, environmental concern is taken to mean having an awareness and concern about the impact of individual actions or behavior on the environment. The results revealed that environmental concern had a significant positive influence on both perceived usefulness and perceived ease of use, and that perceived usefulness had a direct effect on attitude toward car sharing, which in turn affected to behavioral intention toward car sharing. That means environmental concern positively affected intention to use car sharing through perceived usefulness and perceived ease of use. The results were consistent with the study of Barnes & Mattsson (2017); Fleury et al. (2017); Müller (2019); Schlüter & Weyer (2019); Hjorteset and Böcker (2020) and Wang et al. (2020). It can be interpreted that the customers who have environmental protection attitude hold good attitude and motivation towards using car sharing.

Social influence

Social influence in this research refers to how other people influence an individual's behavioral intention (E. S.-T. Wang & Chou, 2014). The results revealed that social influence positively influenced perceived usefulness and perceived ease of use, and indirectly impacted the intention to use car sharing. The findings were in accordance with the theory of reason action (TRA) (Fishbein & Ajzen, 1975) and the studies of Liu & Yang (2018); Mattia et al. (2019); Jing et al. (2019) and Claasen (2020).

Car sharing is a relatively new service in Thailand, which relies heavily on new technology. Thus, people may need in-depth information about such services by consulting their colleagues, friends or family, or they may search for information on the internet or social media to find reviews from real users.

Perceived risk

Perceived risk was a critical obstacle for customers' acceptance of a new technology (D. J. Kim, Ferrin, & Rao, 2008). In this study, perceived risk divided into three types: personal information risk, functional risk and vehicle risk. The results revealed that perceived risk did not influence attitude toward car sharing. This may be because customers were aware of the usefulness of car sharing rather than its risks. On the other hand, perceived risk had a negative direct effect on intention to use car sharing, which was consistent with Lamberton & Rose (2012); Barnes & Mattsson (2017); P. Cheng et al. (2019); Jing et al. (2019); and Wang et al. (2020). That means the risks of car sharing decrease the intention to adopt the service because user might be concerned about their personal information being revealed, or the stability of the systems, or the safety of the vehicles.

Effects of External Variables on intention to use car sharing

The results found that social influence had the highest impact on intention to use car sharing. It seems that consumers will consider car sharing when people around them or famous people use it. One reason may be that car sharing is a new phenomenon in Thailand, so the customers still hesitate to use the service until they have information about it from reliable sources. Cultural norms suggest that Thai people usually rely on other people. Thus, word-of-mouth is very important for Tai customers' decision on car-sharing services.

Meanwhile, perceived risk had the least effect on intention to use car sharing. People may be concerned about the risks associated with the service on both application software and vehicles. However, mobile phone applications have become a part of many Thais' lifestyle so many people have grown used to and trust mobile-apps. Moreover, people may perceive the usefulness of car sharing rather than its risks. Therefore, people may be concerned about the risks but not emphasize them.

5.4 Research implications

The implication of the key findings of this study provided guidelines for decision makers, system developers and stakeholders of car sharing to contribute to the strategic planning of car-sharing systems that will best serve the public for sustainability and economic development.

Firstly, the results from this present study indicated that people tend to use car-sharing for work or study. In addition, walking distance was a significant factor for car sharing determination. In order to satisfy the target group, the drop points should be located near offices or universities (within 500 meters), while drop points should be close to each other, covering all areas of Bangkok.

Demand estimation and replenishment is also important. Based on the results, people tend to wait for an available shared car around 20 minutes. Thus, car-sharing operators should estimate the daily demand of shared cars for each station, together with the relocation plan need to be considered cautiously.

Undoubtedly, the price of the service is a crucial factor in the adoption of car sharing. The price plan of the service should be seen as good value for money. Options of the service should be variety in terms of price plans and vehicle types. So that the customers can choose the optimal plan and service for themselves. Furthermore, in this early stage of car-sharing service operation, promotions, particularly first-time-using promotion, are significant because people are more willing to try the new service when good promotions are on offer.

Moreover, this research highlighted some factors that are important in the adoption of car sharing and the relationship of the factors. Based on the results, a positive attitude toward car sharing was the most important factor. In order to establish a positive attitude to the customer, perceived usefulness is a significant factor. The usefulness in terms of cost saving, convenience, environment and social benefits should be addressing and promoting an awareness of car-sharing services. Furthermore, ease of use is also one of driven factors for perceived usefulness. The system should be designed to enhance the accessibility. In addition, instruction should be created in the form of infographics for an easier understanding for the customers on all platform and promoted to the public.

The results confirmed a significant positive relationship between environmental concern and perceived usefulness that influences to a positive attitude towards car sharing and results in the intention to use car sharing. It means that people with ‘green’ awareness are more inclined to use car sharing. Therefore, car sharing operators should highlight the environmental benefits of car sharing to customers.

People tend to rely on word-of-mouth recommendations from their colleagues, family, friends or famous people. Thus, the technique of share-plan promotion that the group of users can use the same plan or influencer marketing should be adopted to spread awareness.

However, perceived risk still plays a crucial role toward the intention to use car sharing. To decrease customers’ perceived risk of car sharing, it is significant to increase trust. The car sharing operation need to ensure about operation platform both application and vehicles. The security of the application needs to be ensured. Also, the shared cars need to be maintained regularly. Furthermore, a satisfactory cleaning system was seen as a basic requirement in this circumstance of Covid-19 pandemic.

5.5 Research limitations

Both of the surveys were conducted during the Covid-19 pandemic in which people were very concerned about hygienic conditions and social distancing was required in public places. Many people wanted to avoid talking, touching or receiving anything from strangers. To solve this problem, the questionnaire was created in Google form, then a link of the questionnaire generated a QR code. So, respondents were given this QR code to access the online questionnaire. However, some people were still wary of the hygienic conditions and declined to answer the survey.

5.6 Suggestions for future research

The sample of both studies contained a small group of people who had car-sharing experience. For this point, it would be useful to conduct future research to collect the data equally from people with and without car-sharing experience. Moreover, the future research may compare factors influencing the decision to use car sharing from car owner and non-car owner perspective.

The external constructs of technology acceptance are unstable. There are many possible variables, such as facility condition, trust and reliability, relating to the intention to use the new technology. Thus, there are worth to applied different variables to test the relationship between those variables and the intention to use car-sharing services. In addition, future study may examine the moderation effects of personal characteristics and car-sharing experience on the intention to use car sharing.

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